Euskal Herriko Unibertsitatea / Universidad del País Vasco

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Universidad del País Vasco
Euskal Herriko Unibertsitatea

Informatika Fakultatea

Detecting, counting and sizing bluefin tuna schools using medium range sonars of baitboats in the Bay of Biscay

Dissertation presented to the Department of Computer Science and Artificial Intelligence for the degree of Doctor of Philosophy

Presented by

Jon Uranga Aizpurua

Thesis Directors

Dr. Maria Carmen Hernandez Gomez

Dr. Haritz Arrizabalaga De Mingo

Donostia, June 2017

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EUSKO JAURLARITZA
GOBIERNO VASCO

Aitari, Amari, Intzari eta Nereari

Eskerrak

Lehendabizi eskerrak eman nahi dizkiet tesi zuzendariei:

Haritzi, bere lasaitasun eta gertutasunetik emandako gomendio guztiengatik eta eskainitako laguntza guztiagatik. Zientzi mundu honen benetako esanahia erakutsi, proiektu honetan sinistu eta beti aurrera iteko modua aurkitzeagatik, eskerrik asko.

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Published scientific articles:

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- PLOS ONE (submitted).
  Uranga J, Arrizabalaga H, Boyra G, Hernandez MC, Goñi N, Santiago J. *Counting and sizing bluefin tuna schools using medium range sonars of baitboats in the Bay of Biscay*. PloS one. 2017; Submitted.

- COLLECTIVE VOLUME OF SCIENTIFIC PAPERS. ICCAT
  Goñi N, Onandia.I, Uranga J, Arregui I, Martinez U, Boyra G, Arrizabalaga H, Santiago J. *First acoustic survey for a fishery-independent abundance index of juvenile bluefin tunas in the Bay of Biscay*. 2016. SCRS/2015/204.

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  Goñi N, Onandia I, Lopez J, Arregui I, Uranga J, Melvin G, Boyra G, Arrizabalaga H, Santiago J. *Acoustic-based fishery-independent abundance index of juvenile bluefin tunas in the Bay of Biscay: 2015 and 2016 surveys*. 2017.: SCRS/2016/137.

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- Arrizabalaga H., Goñi N, Fraile I., Arregui I., Santiago J., Boyra G., Laconcha U., Uranga J., Santos M., editor. *Investigación para una mejor gestión del Atún Rojo*. V Jornada científica de la Tonyina a L'Ametlla del Mar; 2012; L'Ametlla del mar.

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- Uranga J., Arrizabalaga H., Boyra G., Hernandez Mª, Goñi N. and Urkullu A. 2012. *Automated analysis in tuna long-range sonar signals for fishing vessels*. Time-series analysis in marine science and applications for industry. Brest, France.

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- Goñi N., O. I., Uranga J., Martinez U., Boyra G., Arrizabalaga H., Arregui I., and Santiago J. (2016). *Towards a fishery-independent abundance index for east Atlantic juvenile bluefin tunas: outputs of a directed acoustic survey in the Bay of Biscay*. The Bluefin Futures Symposium, Monterey, California.

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LUIS BARRANKO
HONDARRIBIA

Argazkia: Luis Barrranko arrantza ontzia. 2016.

Laburpena

Atlantikoko hegalaburra (AHL) (*Thunnus thynnus*), hegalmotz edo zimarroi bezala ere ezaguna, atun familiako espezieen artean haundiena da eta, bere eragin ekonomikoaren ondorioz, azken hamarkadetan arrantza industria garrantzitsuen bitartez ustiatu da (Fromentin and Powers 2005). Beita biziko euskal arrantza flotarentzat garrantzi handiko espeziea izan da hogeigarren mendearen erdialdetik gaur egunera arte. Mundu mailan ere gero eta preziatuagoa da AHLa: azkenaldian jasandako arrantza-ahaleginaren gorakada da horren adierazle. 2006an buruturiko populazio ebaluazioak erakutsi zuen, ordea, bai mendebaldeko hegalabur populazioak (Mexikoko golkoan erruten dutenak), bai ekialdekoak (Mediterraneoan erruten dutenak) gain ustiatuta zeudela. Horren harira, atunaren kontserbazioaz arduratzen den erakundeak (ICCAT-Atlantikoko Atunen Kontserbaziorako Nazioarteko Batzordea) berreskuratze plan bat martxan jarri zuen 2007an. Ekialdeko populazioaren egoeraren gainean ziurgabetasuna dago oraindik (Fromentin *et al.* 2014), baina aholkularitza zientifikoan oinarrituriko kudeaketa gauzatua dago gaur egun. Kudeaketa horren bi ardatz nagusiak arrantza kuota zientifikoen ezarketa eta Atlantiko osoko ikerketa programaren bitartez (GBYP) sustatutako ikerketak dira.

Tesi honen ardatza Bizkaiko golkoko hegalaburra da, izan ere, eremu hori espezieko jubenilentzako (nahiz eta helduen presentzia ere esanguratsua izan) elikatze gune garrantzitsua baita (Cort 1990). Bizkaiko golkoak AHLren habitat osoaren zati erlatiboki txikia irudikatzen du (Arrizabalaga *et al.* 2015), baina, hala ere, ipar-ekialdera udan burutzen duten migrazio trofikoko elikatze eremu garrantzitsuena da jubenilentzat (Goñi and Arrizabalaga 2010a). Ikerketa eremua (43-47°N eta 2-6°W) Bizkaiko golkoko hego-ekialdean beita biziko euskal arrantza flotak ekainetik urrira bitartean burutzen dituen jardueren bitartez mugatu da (Uranga *et al.* 2017). AHL urtero ziklikoki burutzen dituen migrazio trofikoen ondoren ikerketa eremutik ez mugitzeko ohitura du, eta bertan geratzen da uda osoan zehar (Arregui I. 2015). Espezie horren portaera eta etengabeko presentzia ikusirik, 1940ko hamarkadan beita biziko arrantza flota garatu zen eta, harrezkero, udako atun arrantza kanpainak gogorki errotuta daude Bizkaiko golkoan (Santiago J 2016).

AHLren populazio kudeaketan, esfortzu unitateko harrapaketa kopuruan (EUHK) oinarrituriko indizeak erabili ohi dira (ICCAT 2016b) ugaritasun erlatiboak lortzeko. Bizkaiko golkoko beita biziko euskal arrantza flotak AHLrentzako ugaritasun indizea garatzeko orain arteko datu kopuru handiena ekarri du (Santiago J 2016). Ekarpen garrantzitsua izan arren, arrantzaren bidez lorturiko harrapaketan oinarrituriko datu serie horiek zenbait eragozpen analitiko aurkezten dituzte (diseinu zientifikoaren falta, korrelaziozko behaketak, ez-zorizko laginketa edo harrapaketa aldakorrak) (Maunder *et al.* 2006) eta, horretaz gain, azken urteetan hainbat eragozpen operazional antzeman dira (2012 eta 2015ean, adibidez, espainiar beita biziko arrantza flotak zegokion arrantza kuotaren %100 saldu zuen). Eragozpen horiek EUHKren datu serieak ahultzen dituzte eta, ondorioz, indize horren bitartez burututako ugaritasun ebaluaketen zehaztasun eta sendotasuna mugatuta geratzen da.

Gaur egun, Bizkaiko golkoko EUHK estandarizatua erabiltzen da Atlantiko ekialde osoko atun jubenilen populazioaren ugaritasun indizea kalkulatzeko (Itoh *et al.* 2012; Rodríguez-Marín *et al.* 2003). Indize horren erabilerak harrapaketa konstantea ontzat ematen du (Gulland 1983), baina hori errealitatean ez da hala izaten; izan ere, ingurugiro efektuek arrainaren distribuzio espaziala alda dezakete eta, arrainaren portaerari dagokionez ere, hainbat faktorek (arrainaren distribuzio bertikala, janariaren eskuragarritasuna, elikadura ohiturak, urdail betetze maila...) aldaketa eragin dezakete. Faktore aldakor horiek EUHK estandarizatua lortzeko prozesuan modu egokian sartzea zaila da eta, gainera, urtetik urtera faktore desberdinek efektu desberdina eragiten dute prozesuan, eta aldakortasun horrek zehaztasun galera dakar ugaritasun indizeak kalkulatzeko orduan (Glass 2000).

Arrantzaren bidez lorturiko harrapaketetan oinarrituriko datuek dakartzaten zehaztasun galerak saihestu beharrak bultzatuta, arrantzetan oinarritzen ez diren ugaritasun indizeak garatu beharra ikusi zen. Zentzu horretan, sistema akustikoak dira arrantza ekosistemak ikertzeko tresna zientifiko egokienak (Koslow 2009), arrantzetan oinarritu gabe modu independentean uretan aurkitzen diren espezie desberdinak antzemateko eta ezaugarritzeko gaitasuna erakutsi baitute. Bizkaiko golkoan arrantza ontzi gehienek erdi-mailako luzera ahalmena duen 90 kHz-eko MAQ sonar omni-direkzionala (360 gradutan neurtzeko prestatutako sonarra) erabiltzen dute AHL bilatzeko lanetarako. Sonarraren konfigurazioari dagokionez, luzera ahalmena tartea itsasoaren eta patroiaren nahien araberakoa den arren, orokorrean 100-300m arteko distantziak erabiltzen dituzte; horizontalarekiko inklinazioari dagokionez, 5-8ºan ezartzen da; eta sonar elektro uhinaren zabalera bertikal zein horizontalak 5ºan finkatzen dira. Arrantzaleek AHL detektatzeko espreski erabiltzen badute ere, sonar hau analogikoa eta ez-zientifikoa da. Irudiak ez dira grabatzen, sonar pantailan aurkeztutako informazio eta xehetasun guztiak irudiak pantailatik desagertu bezain azkar galdu egiten dira, lantzeko aukerarik eman gabe. Galera handia da hori; izan ere, ekipamendu hau euskal flotaren ontzi gehienek erabiltzen dute. Ekipamendu egokia berebiziko informazio iturria izan daitekeela ikusi da.

Hori dela eta, gure proposamena urtero arrantza ontzi kopuru esanguratsu batean, MAQ sonarraren bitartez irudiak grabatu eta orain arte ustiatu gabeko informazio iturri aberats hori baliatzeko metodologia sortzea da. Irudiak, bai Bizkaiko golkoan burutzen diren udako atun arrantza kanpainetan, bai atuna detektatzeko bereziki planeaturiko behaketa kanpaina akustikoetan grabatuko dira. Irudiak grabatzeko sistema merkea, arina, eta instalatzeko erraza da; eta, gainera, ez du arrantza ontziaren lanetan oztoporik eragiten. Zenbait garraiobidetako "kaxa beltz" ak bezala, irudiak modu autonomoan grabatzeko diseinatua dago. Datuak lortzeko prozesuan, garrantzitsuena arrantzaleen kolaborazioa lortzea da. Azken hamarkadetan zientzia eta arrantza gerturatzeko ahaleginak egin dira eta bi arloen arteko komunikazioa landu da (Lopez *et al.* 2014); gaur egun, informazio eta datuen elkar-trukaketa handiagoa daukagula esan daiteke.

Behin irudiak eskuratuta, prozesatzeko sistema bat diseinatu da. Bertan, arrantza operazioak simulatu eta berorietan atun bankuak detektatzeko metodologia bat proposatu da. Metodologian bi pausu nagusi nabari dira. Lehendabizikoan, sailkapen gainbegiratuaren bitartez arrantza ontzietan grabaturiko sonar irudietan AHLren presentzia edo absentzia detektatzea izan da helburua (tesiko lehen kapitulua). Bigarrenean, berriz, behin AHL bankuak morfologikoki detektatzeko gaitasuna balioztatu ondoren, sailkapen ez-gainbegiratua erabiliz, laginketa sistematikoa betetzen duen kanpaina akustiko-zientifiko bateko zein ohiko atun-arrantza egun oso bateko irudietan AHL bankuak modu fidagarrian zenbatu eta neurtzeko metodologia eta beharrezko programak sortzea da (tesiko bigarren kapitulua).

Helburu orokor horiek gauzatzeko bidean, lehen pausua sonar irudiak prozesatu eta beraietatik ezaugarri neurgarriak ateratzeko aplikazio bat sortzea izan da. Programa Java *software*-aren bitartez garatu da, hiru pausu hauekin: aurre-prozesaketa, segmentazioa eta ezaugarri morfologikoen erauzketa. Aurre-prozesaketan, garrantzirik ez duten sonar irudiko zati desberdinak ezabatzen dira. Sonarreko pantailak ikusarazten duen irudiak bi zati desberdin ditu; batetik, sonarra konfiguratzeko menu bat dauka eskuin aldean eta, bestetik, datu akustikoak erakusten dituen ekograma. Lehenengo ariketa, menuari dagokion zatia eta ekogramaren beheko zirkulu erdia ezabatzea da. Behin irudiko eremu horiek ezabatuta, gainerako zatian (ekogramaren goiko zirkulu erdia) zentratzen gara eta garbiketa iragazkiak aplikatzen dira zarata eta sonarrak sartutako beste elementu batzuk kentzeko (ilarak, kurtsorearen gurutzea, itsasontziaren ikurra eta luzera ahalmen tarteen markak) (Uranga *et al.* 2017). Behin sonar ekogramaren erantzun akustikoa garbi daukagula, segmentazioari ekiten zaio. Irudiko pixel guztiak analizatzen dira, zehazteko zeintzuk diren irudiko hondoaren zati (beltz kolorekoak) eta zeintzuk erakusten duten atun taldeari dagokion erantzun akustikoa (koloretakoak). Atuna izateko pixel hautagaiak bereizi ditugunean, 8ko auzokidetasun erregela aplikatzen da irudian eta pixel bakoitza pixel-talde bakar bati esleitzen zaio (pixel-talde hauek *blob* bezala ezagunak dira irudi tratamenduaren komunitatean). 100 pixel baino gehiagoko *blob*-ak baztertu egiten dira. *Blob* bakoitzarekin irudi berri bat sortuko da eta horietako bakoitza atuna izateko hautagai bilakatzen da. Azkenik, *blob* bakoitzarentzako 20 ezaugarri morfologiko ateratzen dira.

Lehen ikerketa honetarako erreferentziazko datu basea AHLren presentzia duten 1.397 irudik eta beste 1.398 ausentziazkok osatzen dute. Irudien aukeraketa behatzaile zientifikoen oharrak jarraituz gauzatu da eta aukeratutako irudiak errealitatean behatu daitekeen kasuistika osoaren (atun bankuak, beste espezieetako bankuak, uhin zaratak, gainazal zarata, beste ontziek eragindako zarata, etab.) erakusgarri izatea espero da. Hasierako datu baseari aurreko pausuan deskribatutako irudi prozesaketa aplikatu ondoren, erreferentziazko datu basea sortzen duten atun presentziazko 1.497 *blob* eta ausentziazko 21.004 atera dira hasierako irudietatik. Ikertutako bi kasu posibleen artean 1/14ko ratioa dago, mota honetako datu baseak “desorekatu” bezala izendatzen dira, eta prozesaketa berezia eskatzen dute. Datu base hori, sailkapen gainbegiratua erabiliz, “atun” edo “ez-atun” bezala etiketatu da, eta jarraian bere portaera neurtu da.

Sorturiko datu basearen ezaugarrien portaera aztertu da jarraian, etiketek adierazitako bi klaseak sailkapen algoritmoen bitartez (ezaugarri morfologikoak erabiliz) sailkatzeko ahalmena neurtzeko asmoz. Horretarako, datu meatzaritza azterketak egin dira: lehendabizi, erreferentziazko datu base desorekatuari bi iragazki aplikatu zaizkio; ondoren, ezaugarri morfologikoen azterketa burutu da eta, azkenik, sailkapen algoritmoen alderaketa azterketa egin da.

Ezaugarrien portaera neurtzeko lehendabiziko iragazkia azpilaginketan oinarritzen da eta absentziazko gehiegizko kasuak gutxitzen ditu (Witten *et al.* 2016). Bigarren iragazkia, berriz, goitiko laginketan oinarritua dago eta presentziazko kasu murritzak gehitzen ditu (Chawla, Bowyer *et al*. 2002). Ondorioz, metodologia neurtzeko garaian hiru datu base erabili dira.

Hurrengo pausuan, irudi prozesaketan ateratako 20 ezaugarri morfologikoak erabiltzearen onurak aztertu dira (bai ezaugarri kopurua, bai horietatik zein den egokiena). Onura horiek aztertzeko ezaugarriak aukeratzeko lau iragazki aplikatu dira: ChiSquared, InfoGain, Support Vector Machine (SVM) eta Stepwise (Witten, Frank et al. 2016). Iragazki bakoitzaren bitartez ezaugarri kopuru txikiagoko datu base murriztuak lortu dira eta horietako bakoitza Random Forest (RF) sailkapen algoritmoa (Breiman 2001) erabiliz prozesatu da.

Datu baseak prozesatzeko metodoa 5 aldiz errepikatutako binakako balidazio gurutzatuan (5x2cv) oinarritzen da. Metodo honekin, itzuli bakoitzean, datu basea zorizko bi zati berdinetan banatzen da, non bata trebatzeko datu basea izango den eta bestea, berriz, azterketa burutzeko datu basea. Emaitzak ebaluatzeko *Kappa* (Wood 2007), *T-test* eta zehaztasuna neurtzeko azterketa estatistikoak aplikatu dira.

Azkenik, ezaugarri kopuru egokiena erabaki ondoren, bost sailkapen algoritmo aplikatu dira aurretiaz iragazitako hiru datu baseetan, eta elkarren artean alderatu: RF (Breiman 2001), SVM (Cortes and Vapnik 1995; Burges 1998), Multilayer Perceptron (MLP) (Bishop 1995; Haykin and Network 2004), Iterative Dichotomiser 3 (J48 *in* WEKA) (Quinlan 1996) eta Instance-Based learner with fixed neighborhood (IBK) (Aha, Kibler et al. 1991) sailkapen algoritmoak. Bakoitzarekin lortutako emaitzak ebaluatzeko sentsibilitate, espezifizitate, Kappa eta AUC indizeak kalkulatu dira. Indizeak prozesatzeko 30 aldiz errepikatutako hamarnakako balidazio gurutzatuan oinarrituriko metodoa aplikatu da (30x10cv). Horrela, sailkapenaren gain-doikuntza bermatzen da eta emaitza egonkorragoak lortzen dira (Kohavi 1995).

Lehen kapituluko emaitzei dagokienez, azken pausuan gauzatutako algoritmoen arteko alderaketa azterketak erakutsi du tesi honetan ezaugarri morfologikoak darabiltzan metodologia jarraituz aplikatutako algoritmo guztiek sonar irudietan AHL egoki sailkatzeko gaitasuna dutela. Emaitzak balioztatzeko aztertutako datu base desberdinen artean emaitza hoberena lortu duena goitiko laginketan oinarrituriko iragazkia izan da. Sailkapen algoritmoen artean, berriz, RF algoritmoak erakutsi du zehaztasun handiena. Aurkeztutako metodologiaren bitartez lortutako emaitzek portaera orokor ona erakutsi dute eta sailkapen modelo morfologiko bat erabiliz (SMM) sonar irudiak “atun” edo “ez-atun” kasu bezala sailkatzeko egokia dela baieztatu da.

Bigarren kapituluari dagokionez, lehendabiziko ekarpena aurreko kapituluan (Uranga *et al.* 2017) balioztatutako atun bankuak morfologia ezaugarrien bitartez SMM a eguneratzea izan da. SMM berriari 2015. urtean Bizkaiko golkoan garatutako kanpaina akustikoan grabatutako 1.273 irudi gainbegiratu gehitu zaizkio. SMM berrituaren bitartez, sailkapen ez gainbegiratua erabiliz, 2015eko laginketa sistematikoa betetzen duen kanpaina akustiko-zientifiko bateko egun oso bateko sonar irudiak “atun” edo “ez-atun” bezala etiketatu dira. Random Forest (RF) motako algoritmoa erabili da (Breiman 2001) eta, aztertutako egunean segundo bateko frekuentziarekin 11.52 ordu grabatu zirenez, sortu dugun datu base etiketatuak 41.496 erregistro ditu.

SMM arekin, denbora tarte osoko (datu basea) denbora instante (erregistro bat segundoko) bakoitzerako etiketa bat lortu dugu. Baina gure helburua “atun” bezala etiketaturiko erregistroak atun banku bakarretan elkartzea da, eta horretarako informazio gehiagoren beharra dago. Sonar irudiek ekogramaz gain beste informazio mota bat ere eskaintzen dute: itsas ontziaren kokapena (latitudea eta longitudea), abiadura, sonarraren luzera ahalmen tartea eta sonarra konfigurazio-irabazi desberdinen informazioa. Irudietatik informazio hori atera ahal izateko Karaktereen Antzemate Optikoan KAO (ingelesezko OCR, Optical Character Recognition) oinarrituriko aplikazio berri bat garatu da. Horren bitartez, irudietako balore alfanumerikoak karaktere digitaletara eraldatzen dira. Horretarako, ondorengo pausuak bete behar dira: irudiko eremu interesgarrien aukeraketa, irudiaren aurre-prozesaketa, eremu interesgarrien segmentazio bertikal eta horizontala, ezaugarrien erauzketa, karaktereen antzematea eta emaitzen balioztatzea (Uranga 2013).

KAO aplikazio berriarekin lortutako informazioa eta aurretik ateratako ezaugarri morfologiko eta “atun” edo “ez-atun” etiketak datu base berri batean batzen dira. Datu base berrian oinarritzen da ondoren garatu den atun bankuak zenbatu eta neurtzeko metodologia. Metodologia berriaren azken emaitzak atun banku kopuru estimatua, kokapena eta neurriak (metro karratuetan) dira. Emaitzen egokitasuna neurtzeko, behatzaile zientifikoek hartutako oharretan ageri diren atun banku errealen kopuru, kokapen eta neurriak hartzen dira kontuan. Orotara, 34 atun banku behatu dira aztertutako egunean zehar, horietatik 21 sonar bitartez eta beste 13ak ekosonda bitartez.

Bankuak zenbatzeko metodologia garatzeko garaian arrantzaleen arrantza portaera simulatu da. Arrantza operazioetan abiadura jaitsi egiten da, eta tokian bertan denbora tarte bat izaten da beita bizia uretara botatzen eta kaina bidez atunak arrantzatzen. Ondorioz, abiadura, denbora eta geo-lokalizazioa izan dira gure datu baseko “atun” etiketak banku bakarretan batzeko irizpideak. Irizpide egokiena aukeratzeko optimizazio testak burutu dira eta, emaitzen arabera, detekzioen arteko denbora izan da bankuak batzeko irizpide egokiena. Irizpide horren bitartez, estimatutako banku kopuruaren eta estimatu/behatutakoaren arteko asmatze tasa handiena lortu da.

Emaitzak balioztatzeko, aukeratutako irizpidearekin, atun bankuak estimatu dira eta behatutako bankuekin alderatu dira. Alderatzeko, konfusio matrize bat sortu da banku estimatu eta behatuekin. Bertatik egiazko kasu positiboak (EP), gezurrezko kasu positiboak (GP), egiazko kasu negatiboak (EN) eta gezurrezko kasu negatiboak (GN) kalkulatu dira. Beraien bitartez sentsibilitate, espezifizitate, iragarpen positibo eta zehaztasun indizeak kalkulatu dira (1, 0.99, 0.75 eta 0.99ko balioekin) eta emaitza orokor egokiak lortu dira. Gure metodologiaren bitartez AHL talde kopuru zehatza estimatu da (34) eta horietako 23, egiazko kasu positiboak (EP) izan dira, %68 zuzen, orokorrean.

Bankuen tamainaren neurriak estimatzeko garaian metodologia berri bat ezarri da. Neurriak sonar irudietako atun banku bezala sailkaturiko *blob*-etatik atera dira eta, patroi bakoitzak arrantzaren beharren arabera sonarraren luzera ahalmen tartea aldatzen duenez, eskala faktore bat aplikatzen zaie. Sonarraren konfigurazio-irabazi desberdinek aldakortasuna sartzen dute neurrien kalkuluan ere, eta hori saihesteko modelo matematikoak erabili dira. Modelo lineal arrunta eta modelo gehigarri orokortua MGO (ingelesezko GAM, Generalized Additive Models) erabili ditugu atun bankuen gainazal estimatuetan konfigurazio-irabaziek daukaten eragina zuzentzeko eta bietan egokiena aukeratzeko Akaike informazio irizpidea AII (ingelesezko AIC, Akaike Information Criterion) indizearen emaitzetan oinarritu gara (Chambers and Hastie 1991). Estimatutako eta behatutako gainazalen balioen antzekotasunak metodologia hau neurketa erlatiboak burutzeko balioztatu du.

Laburbilduz, tesi honetan aurkeztutako aplikazio eta metodologia berriek erakutsi dute teknika eta tresna berriak erabil daitezkeela AHL bezalako espezie pelagikoak monitorizatu eta kudeatzeko, arrantza datuak erabili gabe. Lan honetan, luzera ahalmen ertaineko sonar irudiak landuz AHL behatzeko modu berri bat aurkeztu da. Aurkezten diren atun banku zenbaketa eta neurketa emaitzek, bai udako atun arrantza kanpainetako, bai laginketa sistematikoa betetzen duen kanpaina akustiko-zientifiko bateko irudiak lantzeko gaitasuna erakutsi dute. Testuinguru honetan buruturiko lanek eta lortutako emaitzek, ondorengo urteetan jorratuko diren kanpaina akustikoak eta beraietan hartuko diren behaketak gordetzeko modua estandarizatzeko bidean, informazio baliagarria ekarri dutela uste da. Metodologia honen puntu indartsuenetako bat post-prozesaketa lanen arintzea da, udako atun arrantza kanpaina oso batean zein kanpaina akustikoetan grabaturiko irudiek datu kantitate oso handia sortzen baitute eta horiek lantzeko egin beharreko esfortzua oso haundia baita. Aurkezturiko metodologia honen bitartez ez da denbora tarte osoa analizatu behar eta automatikoki atuna aurkitzeko probabilitate handia dagoen guneetan jartzen da fokua. Aplikabideei dagokienez, metodologiak erakutsitako moldagarritasunak (ohiko atun arrantza kanpainetan zein kanpaina zientifiko akustikoetan probatu da), metodologia beste espezie pelagiko (hegaluzea, adibidez), arrantza eremu (Tropikoko arrantza eremua) edota ekipo akustiko (frekuentzia altuko sonar desberdinak) desberdinetan (Brehmer *et al.* 2006) probatzera bultzatzen gaitu.

Ondorioz, erlatiboki den eta arrantza flota bateko zati esanguratsuan modu estentsiboan aplikatu daitekeen metodologia aurkeztu da. Modu honetan, arrantza ontzietako sonar komertzialak ekosistema pelagikoen behatoki bilakatzen dira eta orain arte ustiatu gabeko datu motekin lan egiteko aukera zabaltzen da. Arrantza datuen menpekotasunik gabe, irudi prozesaketa teknika berriek sortzen duten informazio iturri aberatsa eta datu meatzaritzak eskaintzen duen indar analitikoa baliatuz, gaur egungo AHL ugaritasun ebaluaketak hobetzeko bidean lehendabiziko urratsak eman dira.

Argazkia: Pittar arrantza ontzia, Luis Barrankotik. 2016.

General introduction

In this introductory chapter, once the context in which the PhD thesis has been explained, the aspects that justify and motivate the realization of this PhD thesis are described. In addition, the state of the art is revised in order to establish the correct objectives, which guide development of the methodology to test the initial hypothesis.

Context of this research work

This PhD dissertation is a composition of both artificial intelligence and applied research activities at fisheries acoustics focused on detecting tuna at sonar imagery. It has been developed at AZTI-Tecnalia and the University of the Basque Country, thanks to the support of the Basque Government through PhD grant 0033-2011 to Jon Uranga and grant GV 351NPVA00062 to AZTI-Tecnalia. The main activities of the artificial intelligence are focused at image processing, optical character recognition and at the data mining for classification of images. The research carried out at fisheries acoustics area was englobed by the automated acquisition of sonar imagery onboard fishing vessels at the Bay of Biscay during the tuna fishing campaigns, the acquisition of discriminatory knowledge through sonar images of tuna and other species with the help of skipper and the development of an aggregation algorithm based on a binary tuna database in which tuna presence is detected, counted and sized.

Results from this research have been published in journals and conference proceedings and they lay the structural basis to improve the monitoring of the Atlantic bluefin tuna abundance.

The research activities described in this thesis have been conducted at AZTI, a technology centre located in Pasaia (Basque Country, Spain) expert in marine and food research, committed to social and economic development of the fisheries, marine and food sector, as well as to the study of the marine environment and natural resources in the context of sustainable development. It performs strategic and applied research, providing comprehensive and innovative solutions to customers and generating new knowledge.

AZTI’s vision is to be a scientific and technological organization: excellent and dynamic that generates value through the creation of innovative knowledge, technologies, products and services; At the marine research division, scientific knowledge is provided on the functioning of ocean and coastal systems to attain a sustainable management of their goods and services.

The objective is to achieve a sustainable fishing activity by an economically competitive fleet, with responsible fishing practices. This division is composed of four areas: Marine ecosystems Functioning, Sustainable Fisheries Management, Marine and coastal Environmental Management and Efficient use of Resources (Aquaculture and Marine technologies)

This dissertation work was produced at the Tuna Research group, which is part of the Sustainable Fisheries Management area. It has a strong background and expertise in fisheries data collection, fisheries biology and ecology, fish population dynamics, fishery stock assessment, ecosystem modeling, as well as expertise in mathematics, computer science, statistics and data management. AZTI contributes to the generation of scientific advice as participants of the scientific committees of tFRMOs (ICCAT, IOTC). Similarly, among other research and monitoring activities, AZTI also runs international observer programs for European Purse Seiners fisheries in the Indian and Atlantic Oceans, tagging programs and biological research programs.

Motivation

The Atlantic bluefin tuna (*Thunnus Thynnus*) is a species of the genus Thunnus which gathers some of the most economically important, but also intensively exploited fish on the planet. It is the target species of this work and in the Bay of Biscay (BoB) it is one of the main targets for the live bait Basque tuna fishery. Regarding morphological characteristics this genus is divided in two subgenera: temperate Thunnus and tropical Neothunnus (Díaz-Arce *et al.* 2016). The temperate Thunnus subgenera is comprised by the albacore (*Thunnus alalunga*) and the Atlantic (*Thunnus thynnus*), Pacific (*Thunnus orientalis*) and Southern (Thunnus maccoyii) bluefin tunas. Also, the bigeye tuna (*Thunnus obesus*) has been included into the subgenus Thunnus due to its adaptation to cooler waters (Collette et al., 2001). The Tropical Neothunnus subgenera, it is composed by blackfin (*Thunnus atlanticus*), longtail (*Thunnus tonggol*) and yellowfin (*Thunnus albacares*) tunas.

Morphologically it has the following characteristics: the back is dark blue while lower sides and belly are silvery white; it has 39 vertebrates; 12/14 dorsal spines and 15/15 dorsal soft rays; the first dorsal fin is yellow and the second one is darker; the anal fin is yellow and black and the median caudal keel is black; and another singular characteristic is the shortness of their pectoral fins and the presence of the swim bladder.

Regarding physical features, Atlantic bluefin tuna (ABT) is a very powerful fusiform fish, with a large triangular head (Figure 1). This shape, their strength, swimming speed and their slippery skin provide excellent hydrodynamics, which are valuable characteristics to carry out long ocean migrations. Another special characteristic comes from their combative character, all fishermen show respect when they confront to fish a school of big ABTs because its danger. The scientific name also refers to it, since the Latin *Thunnus* comes from the Greek verb “*thynno*” which means “to rush” (Iñigo 2009).

ABT are at the top of their food chain, they visit waters of the Bay of Biscay in the summer months when the water is warmer. It is a historic feeding ground for them. After summer tuna return to more southerly latitudes. Tunas tend not to move from the study area after trophic migrations performed during consecutive summer cycles and they use to reside in the area during this period (Arregui I. 2015). As their presence was confirmed at the Bay of Biscay waters, since the early 1950s, a live baitboat fishery was developed (Santiago J 2016) and consequently, tuna fishing campaigns currently still remain strongly rooted in the Bay of Biscay.

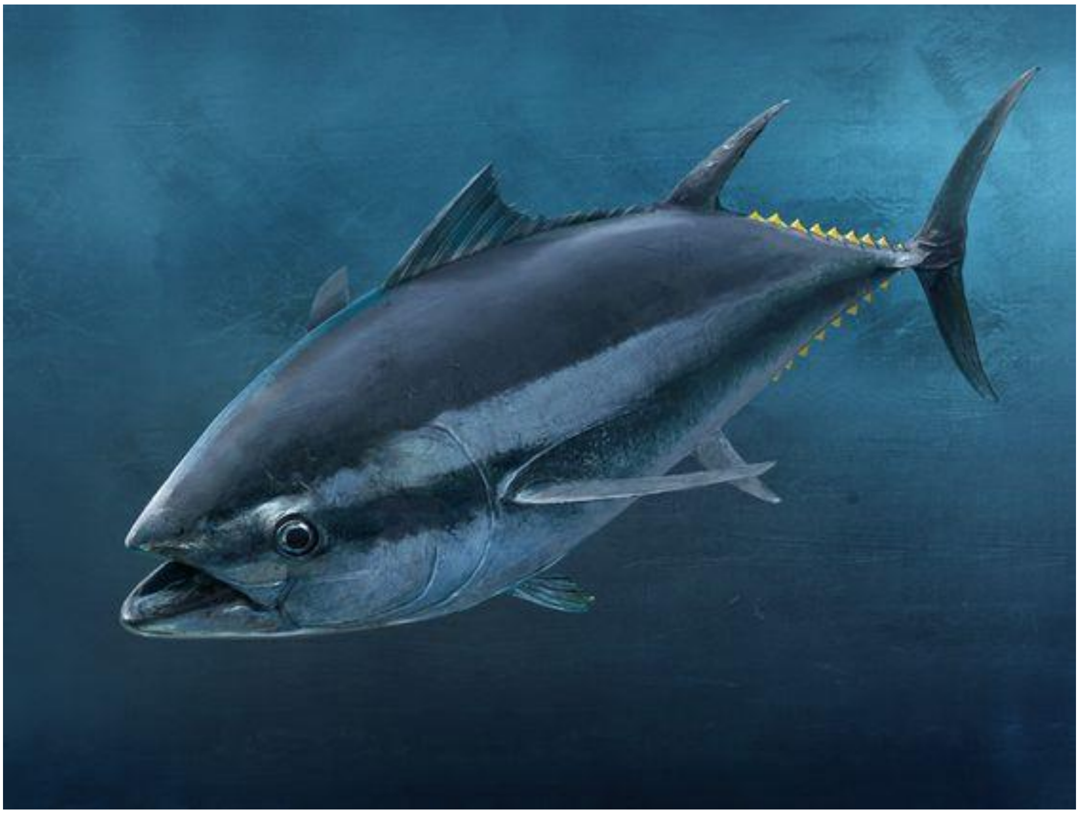

Fig 1

Drawing of an Atlantic bluefin Tuna (ABT) [(1)].

According to ICCAT, the ABT distribution area is composed of two separate populations or "stocks" (BARD 1998; Fromentin and Fonteneau 2001). Their spawning areas are in the Gulf of Mexico and in the Mediterranean Sea for the western and eastern stocks respectively (Figure 2). Moreover, both stocks mix substantially through the Atlantic (Block *et al.* 2005; Rooker *et al.* 2014). Compared to other tuna species it has the widest geographical distribution and the highest tolerance to extreme environmental conditions (Arrizabalaga *et al.* 2015).

Regarding commercialization, fresh tuna is found in the local market during the spring and summer and but it can also be commercialized in various formats (frozen, canned, salting product, etc.). At the international level, the greatest part of the catch is exported to Japanese sushi-sashimi market, where the meat from this species of tuna is highly esteemed and the high price paid for it made ABT exploitation much more profitable than before (Fromentin and Ravier 2005). Due to these advantageous conditions, the equipment of tuna fishery experimented an improvement, causing fishing strategies and efficiency improvements (Liorzou 2001).

(1) (Photograph from National Geographic: http://ngm.nationalgeographic.com/2014/03/bluefin-tuna/img/bluefin-tuna-outside.jpg).

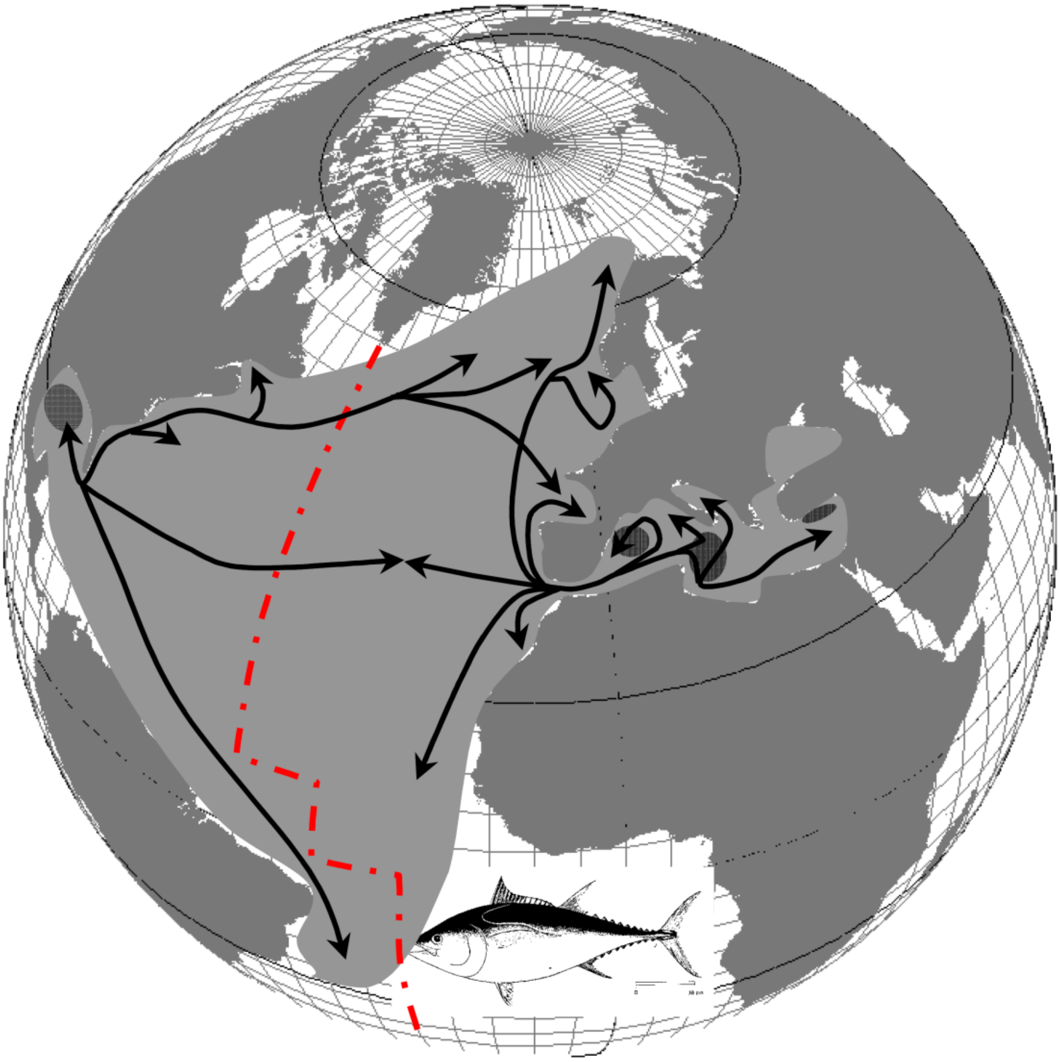

Fig 2

Spatial distribution. Map of the spatial distribution of Atlantic bluefin tuna (blue), main migration routes (black arrows) and main spawning grounds (dark grey) deduced from current and historical fisheries data as well as traditional and electronic tagging information. The vertical dashed line depicts the stock delimitation between the two current ICCAT management units (Fromentin and Powers 2005).

This species has been exploited for several centuries (Fromentin and Powers 2005). First fishing for ABT occurred in the Mediterranean since ancient times when hand lines and beach seines were mainly used (Desse and Desse-Berset 1994). In the nineteenth century beach seines were replaced by traps (Doumenge 1998)and in the twentieth century the hand line fishery targeting juveniles of ABT and albacore tuna at the BoB arose (Bard 1981) and it is still the current technique used by the live baitboats.

Therefore, such an outstanding species with heavy economic and socio-cultural influence should be strictly monitored by scientific and governmental institutions to promote its sustainable exploitation. In this sense, due to its economic importance and the lack of fishery controls the latest stock assessments carried out by ICCAT stablished that both eastern and western stocks had been undergoing heavy overfishing for over a decade (ICCAT 2016b) and currently they are under recovery plans.

Nowadays no direct assessment for the ABT at the Bay of Biscay (BoB) is stablished as the standard official methodology for population monitorization, as is done to asses other important species of the BoB such as anchovy (Boyra *et al.* 2013). Due to the large distribution area and high mobility of the ABT scientific surveys systematically covering the whole distribution area are scarce, and current abundance assessments are based on the catch per unit effort (CPUE) indices. The CPUE index of abundance is based on a fundamental relationship widely used in quantitative fisheries analysis which comply the following formula (Maunder *et al.* 2006):

$$CPUE_t = q \,.\, N_t \qquad \textit{(Equation 1)}$$

Where $CPUE_t$ represent the catch per unit effort at time t, q is the portion of the stock captured by one unit of effort (often called the catchability coefficient) and N is abundance at time t.

CPUE standardization (Maunder and Punt 2004), attempts to standardize effort data to ensure that q can be assumed to be constant, but several factors, such as change in the efficiency of the fleet, food availability, feeding behavior, stomach repletion (Arreguín-Sánchez 1996; Stoner 2004) or the environment affects to its variability.

Our goal is to develop a fisheries independent methodology based on acoustic detections, where the abundance index is not dependent on ABT-fishing. Thereby we propose a detection per unit effort (DPUE) index of abundance that avoids the effect of some factors affecting the catchability that are difficult to standardize. The willingness to eat and stomach repletion of tunas cannot affect the number of acoustic detections (the rest of the effects are further discussed in following chapters). The proposed index assumes that, acoustic detections are proportional to the product of survey effort and abundance:

$$DPUE_t = q \, . \, N_t \qquad \textit{(Equation 2)}$$

Where $DPUE_t$ are the acoustic based detections per unit effort at time t, q is the portion of the stock detected by one unit of effort (here called detectability coefficient), E_t is the effort expended at time and N is abundance at time t.

In this sense, we found answers at the tuna searching methodology used by the Basque live bait fishing fleet, which was observed during boarding on fishing vessels by scientific observers. It can be said that the Basque fleet has “eyes”, because during recent years (1970 onward) sonars have been used to search for tuna (Santiago J 2016). During the summer tuna fishing seasons (from May to September) fishing vessel focus their effort at tuna and all of them use the same tactic. This fact was corroborated onboard by scientists during last years and was the main point that ignited the investigation in this line. Regarding the skipper’s tactic, at first instance, they tend to use radio communication with other fishing vessels, fishermen visual detection, seabirds tracking, etc. while no acoustics are at their disposal. Then, when a tuna school first appears by sonar at medium ranges, they direct towards it and try to confirm the detection with the vertical echo sounder and in positive case, they start the fishing operation.

Thus, in the same way the fleet was capable of detecting schools by sonar, we launched this study to detect the tuna by processing data recorded by medium range sonars (MRS). To do that, we developed an innovative methodology to acquire sonar imagery onboard fishing vessels during fishing campaigns, process them at the end of the season and detect tuna schools. By doing so we want to install sonar imagery data acquisition devices at the mayor part of the fleet and take advantage of the experience based knowledge and the effort of the Basque fleet (sampled area is directly conditioned by the tracks performed by the fishing fleet at searching the tuna). It is indeed a way to boost the collaboration between science and fisheries community through an innovative and economic solution to face the non-addressed problem of the direct assessment based on acoustics for ABT. We believe this teamwork is essential to broaden the range of solutions and to respond to the specific objectives of this thesis.

State of the art

In the scientific literature, several studies have been carried out during the last decades on the fisheries acoustics field. Acoustics has been the main tool to explore new fisheries independent methods to monitor the different fish and aquatic resources. Petitgas et al. (Petitgas *et al.* 2009) presented how to measure stock abundance of many groundfish and small pelagics. They tried to find out what type of assessment does fishery-independent data measured at sea lead to and how could such assessments be useful alongside or instead of existing methods. Presented methodologies were focused at single-species stock assessments and management strategies using only fishery-independent information from research surveys. Methodologies were classified in three categories: monitoring procedures based on indicators of stock attributes, assessment models, and simulation evaluation tools. The general objective was to tackle for ecosystem monitoring and fish stock assessment. In this framework Koslow (2009) established that no research tool is likely to prove as effective as acoustics for sustainable management of fisheries.

At the Bay of Biscay where the bluefin tuna fishing ground is relatively limited (most catches occur within a 2ºx2º box), the scientific acoustic survey might be a good alternative to monitor the ABT presence by designing acoustic based abundance indices which could replace currently performed fishery dependent abundance indices (Goñi *et al.* 2010). According to historic evolution of fisheries acoustics, abundance estimations were first explored by acoustic methods in the 1950s. First studies were focused in counting individual echoes (Tungate 1958; Mitson and Wood 1962). First steps were taken by Dragesund and Olsen who integrated the echo amplitude, but at that time the methodology was imprecise and the target strength of fish uncertain (1965). Scherbino and Truskanov (1966) established that the correct approach was to integrate the intensity and this remains as the fundamental principle of fish abundance estimation. Theoretical and experimental studies carried out in 1970s and 1980s improved the understanding of acoustics and calibration methodologies were set (Foote *et al.* 2005). Vertically deployed echosounders were first calibrated by standardized methods (Simmonds and MacLennan 2008) and used to calculate biomass and target strength measurements of single fish. Split beam echo sounders were used to estimate school densities, dimensions and species discrimination for different species and fishing techniques (Boyra *et al.* 2013; Josse *et al.* 1999). To explore wider distribution areas, devices with broader scopes and larger field ranges were used. Mayer et al. (Mayer, Li et al. 2002) studied limitations of spatial coverage using the traditional single-beam echosounders. According to them, for fisheries acoustics, compared to single-beam, the newly developed multibeam sonar technology, provides larger coverage while maintaining high spatial resolution necessary for schools characterization. However, the large volume of data generated by these systems presents serious challenges for analysis and interpretation. Calibration of this kind of sonar devices was also addressed by Cochrane (2003). According to Gerlotto (2000) multibeam sonar data could be used to estimate fish density and biomass. Combination of echosounder and omni-sonars provided a solution and experiments to explore its utility at stock assessments were run for several species (Misund *et al.* 1996; Misund and Coetzee 2000; Stockwell *et al.* 2012). In this sense Trygonis (2016) demonstrated that horizontal sonars are powerful tools for studying the spatiotemporal distribution of large pelagic schools in the vicinity of drifting FADs.

Fish behavior and vessel avoidance is a theme discussed by various authors. Brehmer et al. (Brehmer *et al.* 2007) studied and analyzed the fish behavior surrounding platforms and fish aggregating devices (FAD). An autonomous sonar buoy prototype equipped with an omni-sonar and video cameras were used to observe behavior of tuna around FADs and drifting objects. This kind of studies are the key to understand behavior patterns of several species and for a proper interpretation of acoustic data related to them. For the herring, Vabø et al. (2002) studied the significance of vessel avoidance behavior during acoustic surveys in Northern Norway. For sardines and anchovies Soria et al. (Soria, Fréon et al. 1996) analyzed vessel influence at the school behavior using a multi-beam sonar and biomass estimates by echo-sounder. Uncertainties in abundance estimates and acoustic density lost were studied. Other species such as *Sardinella Aurita* were analyzed by Gerlotto and Fréon (1992), their vessel avoidance was very limited in comparison to herring schools. In addition to the *Sardinella Aurita* Gerlotto et al. (2004) studied also the three-dimensional structure and avoidance behavior of anchovy in Central Southern Chile. Structures showed to keep a consistent shape and regarding avoidance, while the vertical axis variance was very limited no movements along the horizontal axis were observed. Finally, regarding mackerel, specific swimming depths and non-random migration directions were observed by SIMRAD 24-36 kHz sonar (Godø *et al.* 2004).

Due to the ability of the tunas to migrate over large distances well before an acoustic boat could cover the survey area, not many acoustic direct surveys were used to estimate abundance indices of tunas. To monitor recruitment of age one southern bluefin tuna (*Thunnus maccoyii*) an acoustic sonar monitoring survey was conducted. The acoustic monitoring was followed by the trolling monitoring survey from which thresholds for counting tuna schools were established.

Alternative studies (tagging campaigns, aerial surveys, larval surveys and commercial fleet data) have been carried out in order to improve understanding of abundance patterns necessary for sustainable management of the ABT and other species, but few direct surveys are being conducted specifically for the ABT, generally due to spatial coverage and economic drawbacks.

Acoustic tagging studies were carried out for southern bluefin tuna (*Thunnus maccoyii*) by Hobday (2009) in order to study factors inducing inter-annual variability on abundance index estimates of this species with wide distribution areas. Swimming behavior of fish during the acoustic survey, inter-annual variation in the inshore-offshore fraction, residence time and the juvenile migration percentage should be considered when included in estimating an abundance index for southern bluefin tuna.

Another way of addressing the problem is to use airplanes to provide broad distribution coverage. Patchiness, mobility of the fish and their vessel avoidance behavior are sources of errors in quantitative acoustic surveys and consequently an aerial/acoustic strategy is suggested for this case. Aerial surveys were conducted along 20 days to study the abundance and behavior of bluefin tuna over the Great Bahama Bank region of the Straits of Florida (Lutcavage, Kraus et al. 1998). Aerial/acoustic strategies were also proposed to perform stock assessment of other pelagic fish, the *Sardinops ocellata* (Cram and Hampton 1976). Synchronous aerial observations and vessel measurements were carried out at the Southeast Atlantic. Their combination provided data for a direct estimate of stock size.

Other authors explored alternative methodologies to cover larger areas. Garcia et al. (García, Alemany et al. 2005) focused the research at early life stages. Preliminary results of tuna larval surveys were conducted and data on bluefin and other tuna species larval catches are reported from the Balearic Sea, the Levantine Sea and the Sicilian coasts. The comparative analysis of the bluefin spawning in different areas were used to better understand spawning strategy, larval ecology and identifying population characteristics of bluefin.

The use of commercial fishing fleet and their acoustic data for major coverage and stock assessment is another alternative. Misund and Melvin (Melvin *et al.* 2001; Misund 1997) pointed out that the use of echosounders and sonar data from commercial fisheries should be promoted as the way of quantifying fish behavior and distribution. Brehmer et al. (Brehmer, Lafont et al. 2006) conducted a total of 11 surveys in collaboration with local fisheries, in five regions (Ivory Coast, Venezuela, Senegal, France and Chile), targeting aggregative small pelagic fish. The project surveyed three populations of the clupeid (*Sardinella Aurita*) in continental shelf waters of Senegal, Venezuela and the Ivory Coast. A complete method for continuous data acquisition from aboard a research vessel or commercial boat, with automated data extraction by picture analysis and a data processing method was presented. Aligned with these studies, Dalen (Dalen and Karp 2007) published a collective report of researches published by the International Council for the Exploration of the Sea (ICES), where acoustic data acquisition from fishing vessels is promoted in order to cover major coverage and provide a valuable source of information for fishery management.

Regarding abundance index based stock assessments, works about ABT population evaluation are frequently published by the ICCAT. Latest CPUE evaluations emerged inaccuracies at tracking biomass changes and the last report (ICCAT 2016a) presented by the ICCAT is showing substantial increasing trend over the last years and large fluctuations. Major increases are visible in the Japanese and Mediterranean (Spanish and Morocco) CPUE indicators, which can be related to the recovery plan (ICCAT 2016b) established for this species and the sale of most of the Spanish baitboat quota un the las years. These issues lead ICCAT to highlight the importance of developing fishery independent indices, particularly in light of the difficulty updating the indices used in the assessment with capture data provided by tuna fishery. In this sense, for other species (Boyra *et al.* 2013) inter-annual campaigns has been carried out during last decade to evaluate population changes for small pelagic (*Engraulis encrasicholus*) and for the tuna, the first acoustic campaigns are being launched by Goñi at the BoB (2016).

The field of Artificial Intelligence research (AI) research is adaptive and adjustable, and can provide solutions to almost all the areas of knowledge (Holland 1992) and therefore, we can find, for example, applications in biology and ecology. In this work, we have explored several options such as digital image processing, data mining and optical character recognition applications to detect, count and size bluefin tunas throughout sonar imagery. Image processing can be applied to unimaginable cases, for acoustic based images, sonar images have been analysed by Reid and Simmonds (1993) demonstrating its validity to identify schools and to render an image with the positions of tuna schools. From data recorded by multibeam long-range sonar Trygonis (2009) designed a system for identifying and tracking fish schools, innovative processing algorithms were designed to increase the certainty at fish schools detection. The main data mining techniques used to detect or discriminate species throughout different data sources are the supervised and unsupervised classification tasks. While for tuna is difficult to find automatic image processing tasks, for other species and biological studies, the artificial intelligence has been proven to be useful (Bachiller *et al.* 2012; Fernandes *et al.* 2009; Irigoien *et al.* 2009) to classify the zooplankton and can provide rapid, accurate, species-level classification of bioacoustics data, as done by Armitage (2010) where animal vocalizations from field recordings are classified. In other species, such as Atlantic salmon (*Salmo salar)*, multivariate data analysis was used to discriminate between farmed and wild Atlantic salmon (Aursand *et al.* 2009). Regarding Optical Character Recognition (OCR) technique, historically has been used to scan documents and to become digital images from which to extract the alphanumerical information. and it has been applied in fields such as invoice imaging, legal industry, banking, health care industry, etc. Regarding ecological or fisheries tracking applications, (Brehmer *et al.* 2006) presented a complete method for continuous data acquisition from aboard a research vessel using automated data extraction methods of image and data processing.

In summary, it can be noted in literature that acoustics are pointed as the main tool with the capacity of processing fish and aquatic resources independently and with high accuracy. Therefore, the use of sonar imagery is believed to be an efficient way to address the problem. Several fish behaviour studies were carried out for fish aggregating devices (FAD) of tropical tuna and other species all over the world, but for Eastern Atlantic stock, no relevant studies are available. Several studies regarding issues associated to large spatial areas are available and they all agreed that the use of omni-directional sonars to increase coverage is most appropriate way to address the problem. Concerning alternatives to the currently used CPUE for population evaluations, several studies pointed the necessity of developing independent evaluation methods based in acoustic and in the way of improving accuracy, the combined use of scientific echosounder and sonar (scientific or not-scientific) is promoted. In this sense, the present work is aligned with the objectives of the acoustic community. As regards, Artificial Intelligence (AI) applications in fisheries acoustics, a lack of approaches focused in the tuna is observed at the literature, but nevertheless the adaptability of AI techniques and studies carried out in a variety of species and conditions are showing that they can be a very interesting tool. Therefore, with the aim of getting a DPUE index based on acoustic detections of the bluefin tuna at the BoB, an AI methodology to detect, count and size bluefin tuna schools results to be the best solution.

Objectives and hypothesis

In summary, the estimation of bluefin tuna abundance in the Bay of Biscay using fishery independent methods remains challenging, but new technologies, datasets and approaches provide new opportunities to address the challenge.

To detect the presence-absence of bluefin tuna at MRS imagery recorded on fishing vessels the following objectives were pursued:

- To validate a data acquisition system for medium range sonar whose functioning does not compromise the activity of fishermen.
- To develop an automated image analysis program for medium range sonar imagery recorded onboard Basque fleet vessels, with the aim to extract measurable morphometric characteristics for tuna schools.
- To study the potential of data mining and supervised classification algorithms to detect in a semi-automated way the presence-absence of bluefin tuna in sonar imagery.
- To raise the question about the capability of the methodology to track abundance of juvenile bluefin tuna in the Bay of Biscay and if possible, in which way it could be performed.

For counting and dimensioning bluefin tuna schools the following objectives were pursued:

- To label MRS imagery recorded on an acoustic survey for ABT detection by an morphometric classification model and test its appropriateness for subsequent steps of the counting and sizing methodology.
- To check the appropriateness of using a novel optical character recognition (OCR) application to extract vessel behavior (location/speed) and sonar setup (range, gain) parameters.
- To design a methodology to count the number of school’s and quantify their size, through sonar imagery, image classification models and OCR data.
- To address how a new “detections per unit effort” (DPUE) series could replace the current “captures per unit effort” (CPUE) series for the bluefin tuna population evaluations.

Considering the limitations explained at the state of the art, the current thesis develops several techniques with the aim of complying the following hypothesis:

"Automated analysis of raw medium range sonar imagery recorded onboard fishing vessels allows to automatically detect, count and size bluefin tuna schools in commercial tuna fishing campaigns and scientific acoustic surveys, as a way to improve resource monitoring, scientific advice and ultimately, fishery management of this important resource"

Thesis structure

The PhD dissertation is arranged as follows:

• General Introduction: The purpose of this section is to introduce the context of this research work. The motivation of the study and an up-to-date state of the art are explained to establish the objectives of the presented thesis.

To achieve the objectives defined above the following text has been structured in two chapters based on scientific publications:

• Chapter I: At the first contribution, a methodology for the automated analysis of commercial medium-range sonar signals for detecting presence/absence of bluefin tuna (*Thunnus thynnus*) in the Bay of Biscay is presented. For each sonar image, we extracted measurable regions and analyzed their characteristics. A classification model was built by supervised classification and evaluated its performance by data mining. The discriminatory capacity of sonar images to detect presence and absence was evaluated by statistic indices and results demonstrated that the methodology performed well with commercial sonar imagery, and has the potential to automatically analyze high volumes of data at a very low cost.

• Chapter II: Once the capacity to detect the presence and absence by the classification model was proved by the results of the first contribution, we measured its performance using a full day sonar imagery in a non-supervised way. To do so, we processed the imagery with the same application as in the first paper, we updated the classification model and labelled each time instance of the day as “Tuna” or “No-Tuna”. Extra data (vessel velocity, geolocation, sonar range, tilt and gains) was provided by an OCR application designed to extract interesting character information from sonar images. All data at our disposal was fused in a new dataset and a methodology was designed to count and size unique bluefin tuna schools in a non-supervised way. Results were validated comparing matching ratios between estimated detections with observations annotated by scientific observers during acoustic surveys. Detected schools could serve in the near future to build a new DPUE index for the Bay of Biscay that could replace the currently used CPUE index in ABT stock assessments.

- General discussion and conclusions: this section discusses the main findings and future lines of research are identified. It also lists the main conclusions drawn from the presented contributions. In addition, the answer to the working hypothesis, i.e. the Thesis, is given.

Argazkia: Beita biziko arrantza. Luis Barranko. 2016.

Chapter 1

Detecting the presence-absence of bluefin tuna by automated analysis of medium-range sonars on fishing vessels

1.1 Abstract

This study presents a methodology for the automated analysis of commercial medium-range sonar signals for detecting presence/absence of bluefin tuna (*Thunnus thynnus*) in the Bay of Biscay. The approach uses image processing techniques to analyze sonar screenshots. For each sonar image, we extracted measurable regions and analyzed their characteristics. Scientific data was used to classify each region into a class ("tuna" or "no-tuna") and build a dataset to train and evaluate classification models by using supervised learning. The methodology performed well when validated with commercial sonar screenshots, and has the potential to automatically analyze high volumes of data at a low cost. This represents a first milestone towards the development of acoustic, fishery-independent indices of abundance for bluefin tuna in the Bay of Biscay. Future research lines and additional alternatives to inform stock assessments are also discussed.

Keywords: Sonar, image analysis, supervised classification, bluefin tuna, abundance.

1.2 Introduction

The Atlantic bluefin tuna (*Thunnus thynnus*) is an emblematic species exploited for several centuries that has supported economically important industrial fisheries (Fromentin and Powers 2005). The International Commission for the Conservation of Atlantic Tunas (ICCAT) manages two Atlantic bluefin tuna stocks, the western stock that spawns in the Gulf of Mexico, and the eastern stock that spawns in the Mediterranean. Both stocks have been overfished in recent decades (ICCAT. 2013) and currently they are under recovery plans. Furthermore, the scientific community has warned about the large uncertainty surrounding the eastern stock status (Fromentin *et al.* 2014), which is being addressed with a set of research programs under the Atlantic-wide Research Programme for bluefin Tuna (GBYP) promoted by ICCAT. In order to be able to quantify the effects of the implemented recovery plan, it is of outmost importance to be able to monitor changes in abundance and stock status through accurate indicators.

Fisheries independent scientific surveys are used to monitor the stock abundance of many groundfish and small pelagics (Petitgas *et al.* 2009). Absolute and relative stock abundance estimates are useful to inform management of exploited fish stocks. Many of the uncertainties associated with our ability to estimate fish stock abundances can be linked directly to limitations in the spatial coverage of our sampling systems (Mayer *et al.* 2002). For example, in the case of scientific acoustic surveys, highly precise narrow vertical beam acoustic equipment might fail to detect aggregations if these are sparsely distributed or if fish are aggregated in the unsampled surface. In such situations, the use of commercial fishing vessels and their acoustic equipment allows for substantial increase in the spatial coverage. In fact, major progress has been made in the use of this information as the basis for stock assessment (Brehmer *et al.* 2006; Dalen and Karp 2007; Melvin *et al.* 2001; Misund 1997), as well as to analyze fish behavior (Brehmer *et al.* 2007), vessel avoidance (Gerlotto and Fréon 1992) and fish distribution (Melvin *et al.* 2002).

In tuna stock assessments, time series of standardized catch per unit effort (CPUE) indices are used as proxies for relative abundance. However, these series, based on fishery data, have known analytical challenges, such as lack of scientific design, correlated observations, non-random sampling or variable catchability (Maunder *et al.* 2006), and do not necessarily reflect trends in population abundance. In the case of bluefin tuna, the drastic reduction in fishing opportunities as part of the recovery plan has affected the CPUE indices, and the

Standing Committee on Research and Statistics (SCRS) of ICCAT has recommended urgently developing fisheries independent indices of abundance (ICCAT 2016b).

There are very few fishery-independent surveys for tuna, and other highly mobile species with wide distributional ranges, because the cost associated with research vessels covering the whole distribution area is prohibitive. Moreover, it is not possible to account for the uncertainty associated with this type of surveying (e.g. double counting). Therefore, some fishery independent surveys for tuna have focused on early life stages (larvae) or spawners whose distributional range is much more concise and spatially limited to spawning areas (García *et al.* 2005). When the focus has been on juveniles and adults (with high migration capabilities) airplanes have been used instead of research vessels to provide broad distribution coverage in reasonable timeframes and with reasonable costs (Antonio Di Natale and Justel-Rubio 2014; Lutcavage *et al.* 1998), estimating the approximate horizontal shape of the visible portion of schools (Weber *et al.* 2013). Some sonar and echosounder-based acoustic surveys have also been implemented to monitor southern bluefin tuna recruitment (Itoh and Tsuji 2004), together with trolling transects surveys (Itoh *et al.* 2012).

The standardized CPUE of the Bay of Biscay baitboat fleet is used as the only abundance index for the juvenile fraction of the entire eastern stock (Rodríguez-Marín *et al.* 2003; Santiago J 2016). Catchability by baitboats can be affected by several factors including food availability, feeding behavior and stomach repletion (Arreguín-Sánchez 1996; Stoner 2004). These variables are difficult to incorporate during the CPUE standardization process. Consequently, inter-annual variability could induce bias in the abundance indices (e.g. a large tuna biomass could yield a low baitboat CPUE if plenty of food is available in the environment and tunas are not attracted by the bait). However, Bay of Biscay baitboats use Omni-mode Medium Range Sonars (MRS) to search for tuna, and omni-directional sonars have proven to be useful tools for characterizing large pelagic schools (Arreguín-Sánchez 1996; Miquel *et al.* 2006; Stoner 2004; Trygonis *et al.* 2016). Thus, the information obtained by these sonars could provide data about the number and size of tuna schools in the search area, independent of food availability and feeding behavior. These sonars are analog and non-scientific, used only for display, and all the information collected is lost as soon as it disappears from the screen. Thus, our approach is to record sonar screen shots in a large number of fishing vessels during the tuna fishing campaigns and design an automated methodology for analyzing these images as a way to utilize the data currently wasted. The automated processing of images has been proven to be useful in biological studies and it is a fast-evolving area of research (Bachiller *et al.* 2012; Fernandes *et al.* 2009; Irigoien *et al.* 2009).

In summary, the estimation of bluefin tuna abundance in the Bay of Biscay using fishery independent methods remains challenging, but new technologies, datasets and approaches provide new opportunities to address the challenge. The main objective of this study is to develop an automated image analysis procedure for detecting presence-absence of bluefin tuna in commercial sonar images, plus a validation of the procedure based on data mining. The utility of the procedure to track abundance of juvenile bluefin tuna in the Bay of Biscay is also discussed. This constitutes a first milestone towards the longer-term objective of developing new fishery independent indices of abundance for Atlantic bluefin tuna based on acoustics.

1.3 Materials and Methods

The research presented in this manuscript involved no endangered or protected species. No experimentation with animals was performed and no specific field permits were required as the scientific observations were conducted on commercial fishing activities regulated by the International Commission for the Conservation of Atlantic Tunas (ICCAT). No other ethical issues applied to the present research project.

The study area is delimited by the activity of the baitboat fleet in the southeast corner of the Bay of Biscay, between 43-47°N and 2-6°W, from June to October (Fig 1-1). The Bay of Biscay represents a relatively small fraction of the total bluefin tuna habitat in the Atlantic (Arrizabalaga *et al.* 2015). However, it is the most important known feeding area for juveniles during their feeding migration to the Northeast Atlantic around summer (Goñi and Arrizabalaga 2010a).

Pole and line fishing with live bait is the traditional fishing technique used by the Basque fleet fishing for bluefin tuna in the Bay of Biscay since the early 1950s. Live bait (mainly small horse mackerel, sardine, mackerel and anchovy) is caught with a small purse seine and kept in water tanks onboard. Tuna schools can be spotted visually at large distances and then detected acoustically by sonar, once the school is within the detection range of the sonars. When the boat is close to the tuna school, live bait is thrown into the water to keep the tuna next to the boat, while the boat sprays water so that it is not seen by the tuna. At this point, baited hooks are used to catch the tuna.

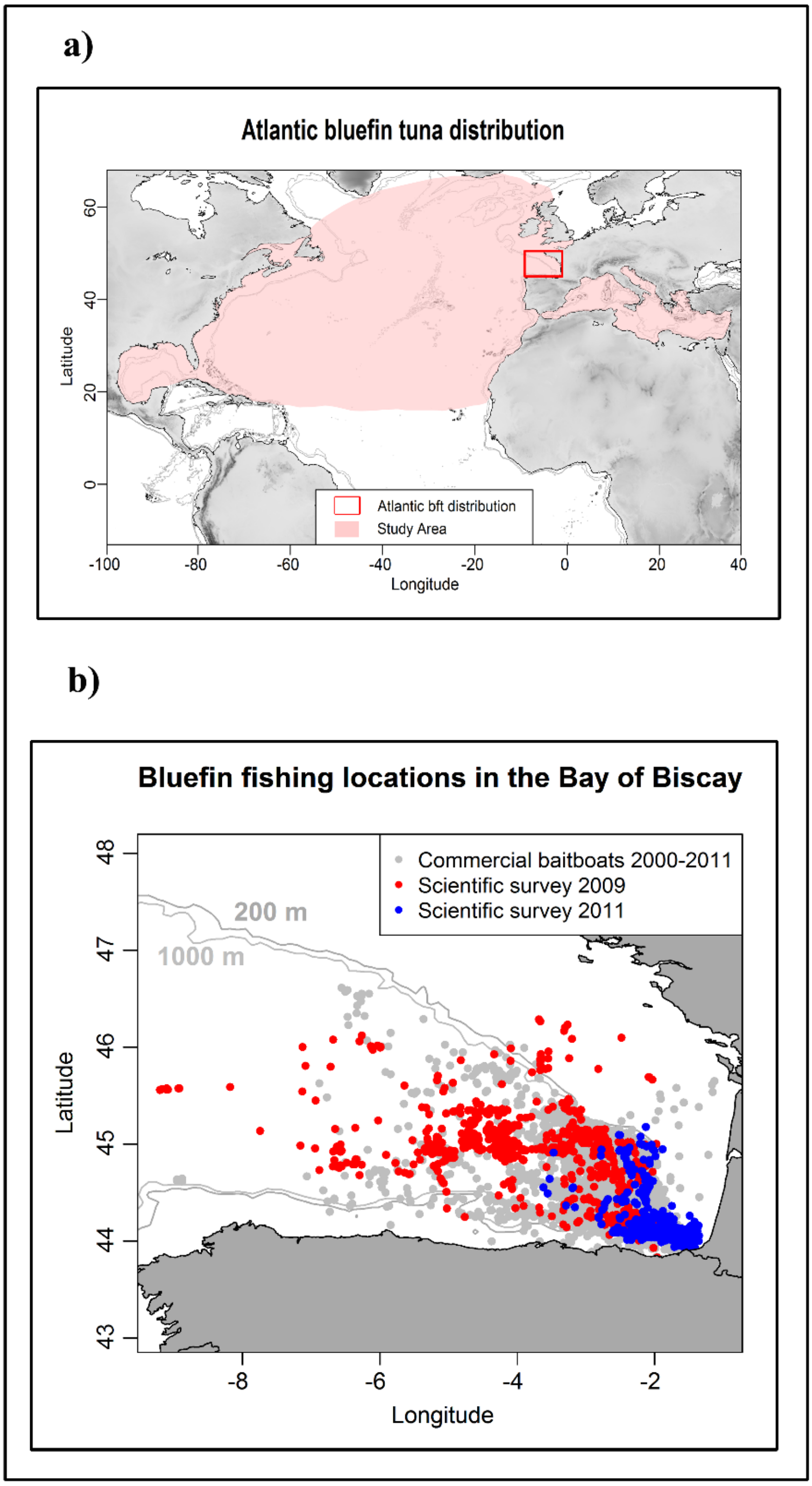

Fig 1- 1

The study area. A) Atlantic bluefin tuna distribution based on ICCAT catch data for the period 2000-2013 (ICCAT 2016b). B) The study area, bluefin tuna fishing locations based on logbook data (Santiago J 2016) and scientific surveys conducted in 2009 and 2011.

In this study we created a reference dataset of sonar images with known categories ("tuna" or "no tuna", based on tuna presence and absence data observed by scientists) to validate an image analysis and classification procedure. This dataset was used to test the methodology developed in this study which consists of several steps: 1) Image acquisition and categorization based on scientific data, 2) Features extraction, 3) Training dataset elaboration and 4) Model training and evaluation.

1.3.1 Image acquisition and categorization based on scientific data

The images processed in this study were obtained from the commercial sonar MAQ 90 kHz. This omni-directional MRS is used by the majority of the Bay of Biscay baitboat fleet. The searching range of the sonar varies with sea conditions and skipper preferences but, in general, range settings of 100-300 m are used when searching for tuna, with a slight tilt of minus 5-7º off the horizontal and narrow vertical and horizontal beam widths (5º).

The screen dumps were acquired using an image acquisition device composed of 400MHz video splitter, an external VGA Capture Device and a laptop with a script for continuous data acquisition. The images selected for this study correspond to six different trips from two scientific tuna surveys conducted in summer 2009 and 2011. The scientific surveys were conducted using a baitboat that behaved similar to the rest of the commercial baitboat fleet. Thus, the area searched during the scientific surveys significantly overlapped the fishing area used by the commercial fleet (Fig 1-1). The main activities conducted by the scientists during the surveys were characterization of the vessel activities, recording of MAQ sonar screenshots and SIMRAD EK 60 signal, tuna tagging and biological sampling (length measurements as well as collection of genetic tissue). The presence of bluefin tuna in the sonar was validated when bluefin tuna was the only specie caught during fishing operations. Presence of bluefin tuna was annotated in the scientific logbooks, and this information was used to classify the images under "tuna" and "no tuna" categories. For this study, the reference dataset was built by selecting a balanced set of images, with 1397 images of bluefin tuna presence and 1398 images of bluefin tuna absence. Bluefin tuna absence was defined as lack of tuna echo in the image and lack of tuna catch. With the aim to include the main types of images recorded, the reference dataset included images with different background colors as well as images with and without surface noise (Fig 1-2).

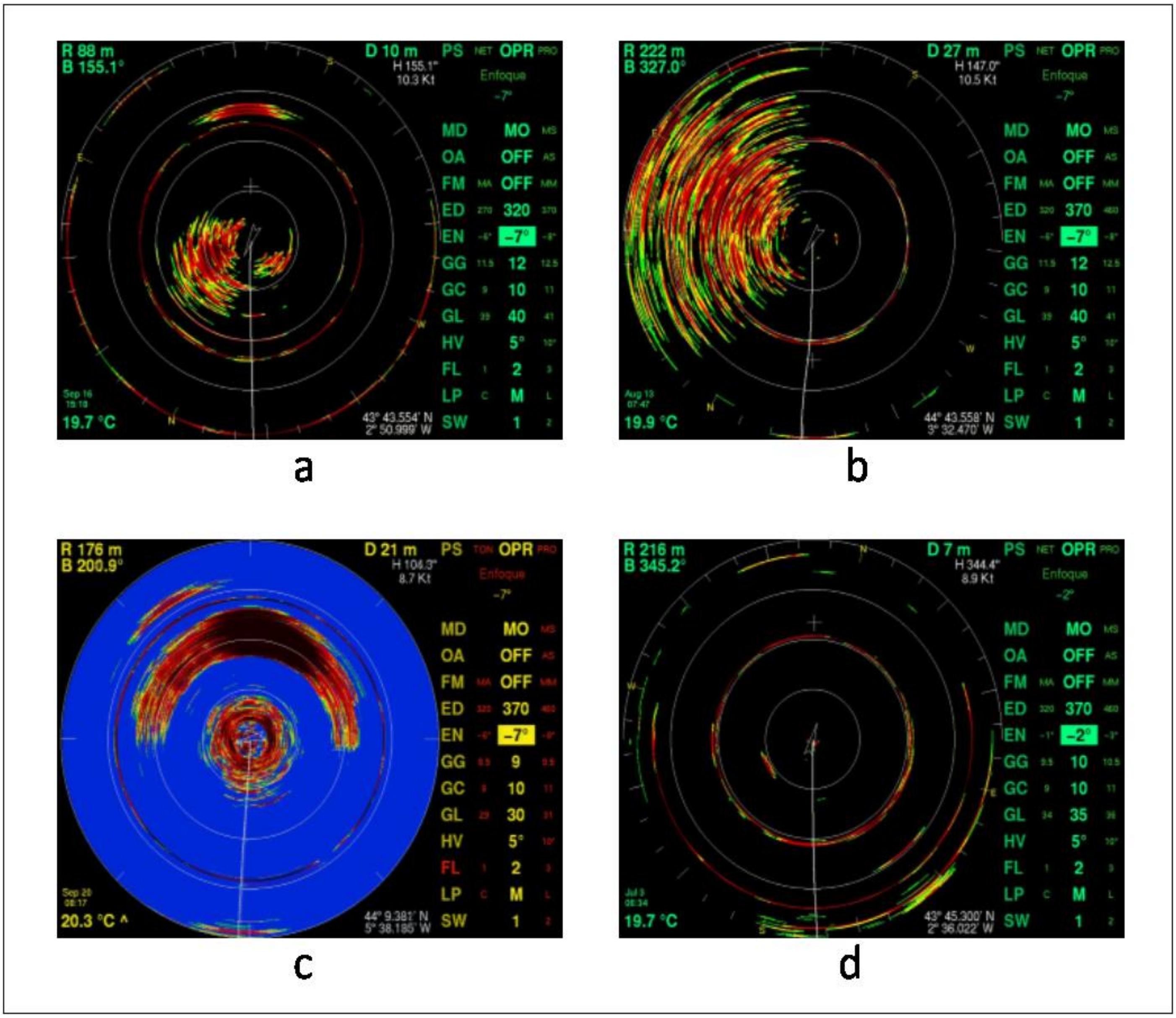

Fig 1- 2

Main types of images recorded. Typical cases of echograms: tuna, black background (a); no tuna, noise (b); tuna, blue background (c) and no tuna (d).

1.3.2 Features extraction

The image processing application was developed with a Java software and it consisted of three steps: (i) pre-processing, (ii) segmentation and (iii) extraction of characteristics.

(i) Pre-processing

The pre-processing phase removed the non-relevant parts of the sonar screen image. The screen of the MAQ sonar has two main regions, the echogram display circle and the menu panel (Fig 1-2). The menu panel provides user information on the operation and system control settings whereas the echogram represents the acoustic data. During the pre-processing we divided the sonar screen into these two basic regions and then focused on the echogram. In the echogram, we worked with the upper half of the circle, as the tuna schools are not clearly detected in the lower half due to the vessel's wake. Furthermore, the schools were observed to appear first in the upper part of the echogram because the vessels move faster than the fish. The sonar display was set up in such a way that the forward observations were located at the top of the screen. Additionally, the echogram was cleaned of noise and sonar display lines and marks, such as cursor crosses, vessel tracks or range circumferences were removed from the echogram (Fig 1-3).

(ii) Segmentation

In the segmentation phase, the selected part of the echogram was partitioned into sub-images or blobs. First, the zero-valued (i.e., black) pixels were considered background and removed; whereas the non-zero (i.e., colored) pixels were grouped, using the 8-adjacency rule, into blobs. Then, in order to reduce the size of the training dataset, the blobs containing less than 100 pixels were removed. We believe that this decision is conservative since the smallest tuna school observed by expert judgement in the reference dataset contained 415 pixels, and so it does not restrict the utility of the classification algorithm developed.

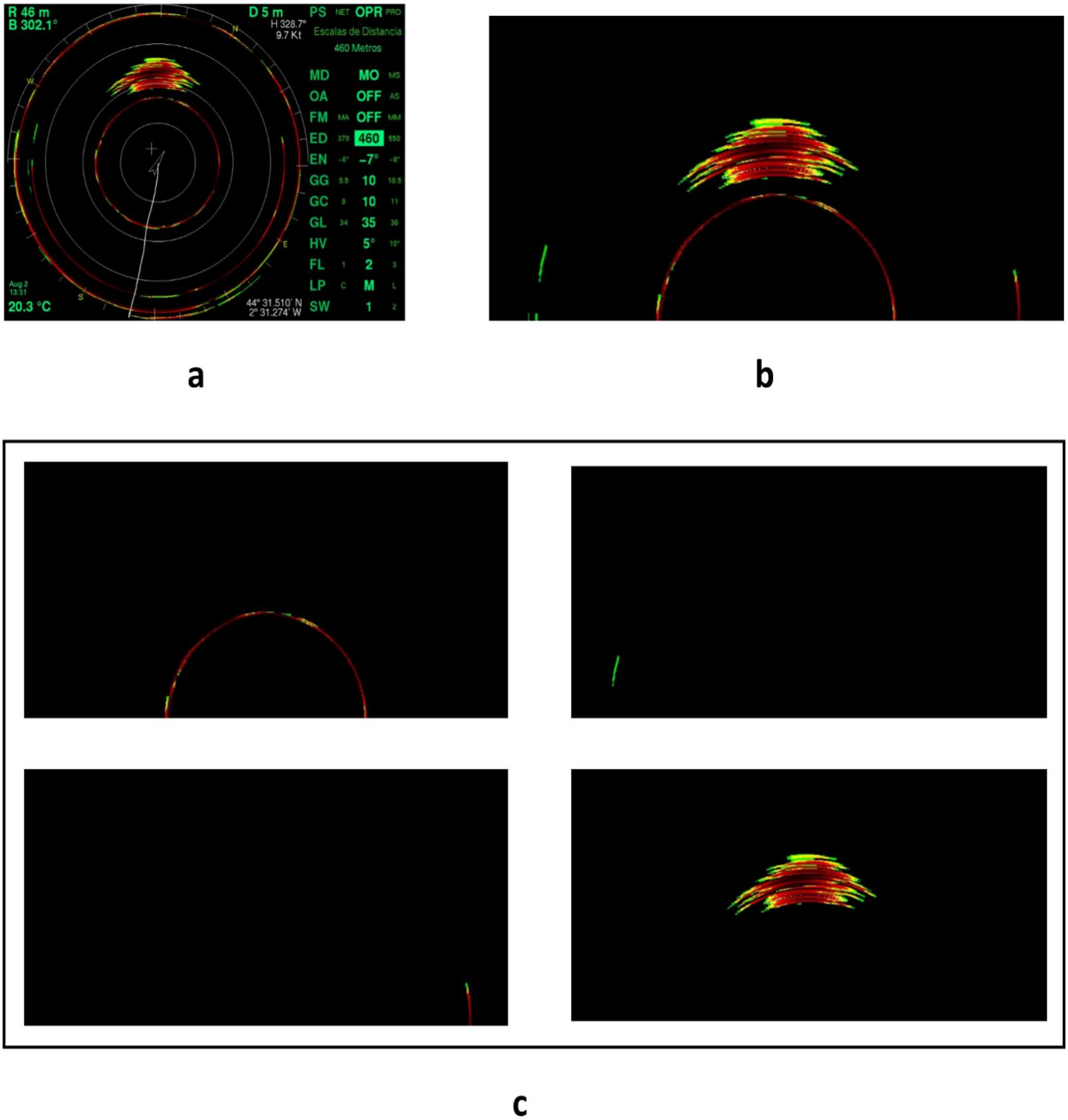

Fig 1- 3

Image pre-processing phase. Sequential steps of the features extraction procedure: (a) original image, (b) image pre-processing, and (c) segmentation of the operative part of the echogram into “blobs”.

(iii) Extraction of characteristics

The remaining blobs were considered tuna candidates and were subject to a characteristics extraction process. For each one, 20 morphologic characteristics were measured related to area, perimeter, position, smallest rectangle containing the blob, best ellipse fitting the blob, aspect ratio, circularity, solidity, greatest distance between any pair of pixels of the blob (known as Feret or Feret's diameter), the projections of Feret's diameter on the axes, the angle of Feret's diameter with respect to the horizontal axis and the minimum value of the Feret's diameter. Finally, the blobs were labeled with two possible categories: "tuna" and "no-tuna", according to scientific observations.

1.3.3 Training dataset elaboration

Based on the reference images, a training dataset of blobs was created to train automatic classification programs and to test their efficiency before they were used to classify new unsupervised images (e.g. those collected onboard commercial fishing vessels without an observer onboard). The training dataset included the categories "tuna" (presence) and "no-tuna" (absence), and is available as S1 Dataset.

S1 Dataset. Complete training dataset of tuna and no-tuna blobs. "Blob_ID" is a unique blob identifier (as a concatenation of survey, year, time and blob number); "Area" and "Perimeter" of the blob are in number of pixels; "BX" and "BY" refer to the upper left corner coordinates of the smallest rectangle housing the blob; width and height refer to the dimensions (in pixels) of such rectangle; "X", "Y", "Major", "Minor" and "Angle" refer to the coordinates of the centroid, the size of the principal and secondary axes, as well as the angle (with respect to the horizontal axis) of the best fitting ellipse; "Circularity" is proportional to the ratio between the area and the squared perimeter, with a value of 1 representing a perfect circle and a value of 0 representing an increasingly elongated shape; Feret's diameter, or "Feret" is the longest distance between any two points along the selection boundary, also known as maximum caliper; "FeretAngle" is the angle (0-180 degrees) of the Feret's diameter and "MinFeret" is the minimum caliper diameter; "FeretX" and "FeretY" refer to the starting coordinates of the Feret diameter; "Aspect Ratio" (AR) is the ratio between the primary and secondary axes of the fitted ellipse; "Roundness" is the inverse of AR; "Solidity" is the ratio between the area and the convex area of the blob; and "Class" refers to the "tuna" or "no-tuna" category.

From the 1397 presence and 1398 absence images in the reference images, after the features extraction, we obtained 22501 blobs for constructing the training dataset: 1497 were positive examples (presence) and 21004 were negative examples (absence), as shown in Table 1-1. The resulting ratio between positive/negative instances was 1/14.03, which shows that we had an unbalanced training dataset, due to the fact that images with tuna blobs also contained many other blobs that were not tuna. Subsampling and oversampling methods are available to manage unbalanced datasets (Zarauz *et al.* 2008). For this purpose we applied a Synthetic Minority Oversampling Technique (Chawla *et al.* 2002) to oversample the minority cases and a Spread Sample filter (Witten *et al.* 2016) to subsample the majority instances with the Weka software (Hall *et al.* 2009).

As a result, we constructed three training datasets: a complete dataset (TOTAL) with 22501 instances; (ii) an oversampled dataset (SMOTE) with 23998 instances; and (iii) a subsampled dataset (SPREAD) with 11999 instances, with 20 morphological characteristics in each one (Table 1-1).

Table 1- 1

Presence/absence ratios. Ratios between presence and absence cases for the three databases: the original database (TOTAL), a subsampled database (SMOTE) and an oversampled database (SPREAD).

	Tuna	No Tuna	Ratio
TOTAL	1497	21004	14.03
SMOTE	2994	21004	7.02
SPREAD	1497	10502	7.01

1.3.4 Model training and evaluation

A first experiment was performed to evaluate the merits of using only some of the 20 characteristics available in the dataset. We compared the classification performance of the reduced datasets containing a subset of characteristics with the performance of the dataset containing the whole set of characteristics. The subset of characteristics in the reduced datasets were selected using four attribute selection filters: ChiSquared, InfoGain, Support Vector Machine (SVM) and Stepwise (Witten *et al.* 2016). The Stepwise method provided an optimum number of characteristics (13 in our case), while the rest of the attribute selection filters were applied at fixed numbers of characteristics (ranging between 3 and 19 in steps of 2). In each case, the attribute selection filter selected the most powerful combination of characteristics. On the reduced datasets, we applied the “five replications of two-fold cross-validation” methodology (5x2cv). With this methodology, in each of the five replications, the available data were randomly partitioned into two equal sized datasets, a training dataset and a testing dataset, so that each data point had a chance of being validated. Using the Random Forest (RF) classification algorithm (Breiman 2001), a classification model was generated with each training dataset and validated on the testing dataset (Dietterich 1998). To compare their relative performance, the Kappa (Wood 2007) and Accuracy values of the reduced datasets were compared to those of the complete dataset. A corrected resampled t-test was also performed to test the null hypothesis of whether the classification with the reduced dataset yielded the same accuracy as when using the complete dataset. This experiment was run under R (RCore 2013), making calls to Weka software. BioSeqClass (Witten *et al.* 2016) and MASS (Venables and Ripley 2013) packages were used for this purpose.

Once the optimum number of characteristics was determined, five classification methods were applied to each of the three different datasets (TOTAL, SMOTE and SPREAD): RF (Breiman 2001), SVM (Burges 1998; Cortes and Vapnik 1995), Multilayer Perceptron (MLP) (Bishop 1995; Haykin and Network 2004), Iterative Dichotomiser 3 (J48 in WEKA) (Quinlan 1996) and Instance-Based learner with fixed neighborhood (IBK) (Aha *et al.* 1991). RF, MLP, IBK and J48 classifications were applied using Weka software and the SVM was applied using R software.

To evaluate the effectiveness and efficiency of classification methods we estimated the average validation indices for sensitivity, specificity, Kappa and Area Under the Curve (AUC). These validation indices are calculated using a confusion matrix which evaluates the predictive accuracy of presence-absence models on a set of test data for which the true values are known. The confusion matrix is defined by the true positive rate (TP, presence was correctly predicted by the model), the true negative rate (TN, absence was correctly predicted by the model), the false negative rate (FN, the model incorrectly predicted absence) and the false positive rate (FP, the model incorrectly predicted presence).

Sensitivity and specificity were calculated by the caret R package (Kuhn 2008), as follows:

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad \text{(Equation 1)}$$

$$\text{Specificity} = \frac{TN}{FP+TN} \quad \text{(Equation 2)}$$

Sensitivity measures the efficiency of the algorithm in correctly classifying positive cases, and specificity measures the efficiency of the algorithm in correctly classifying negative cases.

Kappa and AUC, both are calculated by the PresenceAbsence R package (Freeman and Moisen 2008). Kappa is a measure of agreement between the classifications and the true classes. It's calculated as the difference between the relative observed agreements (p_o) and the relative agreements expected by chance (p_e) divided by the maximum possible agreement: It is known as the "chance-corrected proportion of agreement" (Wood 2007) and it is calculated as follows:

$$Kappa = \frac{p_o - p_e}{1 - p_e} \quad \text{(Equation 3)}$$

AUC, is a common evaluation metric for binary classification problems and represents the area under the receiver operating characteristic (ROC) curve (Fawcett 2006). ROC graphs are two-dimensional graphs in which the TP rate is plotted on the Y axis and the FP rate is plotted on the X axis. It ranges between 0 and 1. When the classifier is very good, the TP rate will increase quickly and the area under the curve will be close to 1. If the classifier has a random behavior, the TP rate will increase linearly with the FP rate and the area under the curve will be close to 0.5.The scale most commonly used for model evaluation implies that a model with an AUC value of 0.95 or higher is excellent; between 0.85 and 0.95 is good; between 0.75 and 0.85 is acceptable; and below 0.75 is poor (Fawcett 2006).

The validation indices (Kappa, Sensitivity, Specificity and AUC) were computed after executing 30 runs of the classification algorithm with 10-fold cross-validation in order to avoid overfitting and to achieve stable results (Kohavi 1995).

1.4 Results

In the first experiment, the characteristics that were most consistently selected by the different attribute selection filters were *Area*, *Major* and *Minor* (Fig 1-4), which are correlated, suggesting that the size of the blob is most informative about the tuna or no-tuna category. However, both Kappa and accuracy values increased as the number of characteristics increased. The trends for both Kappa and accuracy were similar: highest gains occurred for reduced number of characteristics (up until 9), but classification performance continued to gradually improve afterwards, albeit at lower rates. Overall, none of the reduced datasets (including only a subset of the characteristics) improved the performance of the complete dataset. According to statistical t-tests, a similar performance was achieved only when a high number of characteristics were included in the reduced dataset (17 or 19 characteristics, depending on the attribute selection method, Fig 1-5). Thus, since our main goal was to achieve the best classification performance, and computing time was not a limiting factor, we decided to use the complete dataset (with 20 characteristics) instead of a reduced dataset.

Regarding the bluefin tuna classification study, with the original dataset (TOTAL), acceptable results were obtained for all algorithms (Fig 1-6). AUC values were between 0.87 and 0.97 with a difference in performance between algorithms of around 10%, such as between SVM and MLP. Sensitivity estimates varied between 0.73 and 0.79, indicating that all algorithms classify positive ("tuna") instances with similar efficiency. For specificity, all algorithms obtained very high results (> 0.95) with minor differences between them. Consequently, most negative ("no tuna") instances were correctly recognized. Kappa values also ranged from 0.74 to 0.79, thus evidencing good ratios between true positives and true negatives.

For both SPREAD and SMOTE, due to the use of more balanced datasets, the results generally improved for all the indices. This was not the case for the specificity, which showed lowest variation between datasets, and were high (> 0.95) in all instances.

With the SPREAD dataset, the performance of the different algorithms (as measured by AUC and sensitivity) improved with respect to the TOTAL dataset. AUC estimates ranged between 0.90 and 0.98 and were higher than with the TOTAL dataset in all instances. Sensitivity values varied from 0.82 to 0.86 and the lowest value was higher than any of the ones obtained with the TOTAL dataset. Although highest specificity and Kappa were scored by SVM, highest sensitivity and AUC values were scored by the RF.

Finally, the SMOTE dataset obtained the best general accuracy, especially in terms of sensitivity, Kappa and AUC, since scores for these three indices where higher than those obtained with the TOTAL and SPREAD datasets, in all cases. AUC, Kappa and sensitivity values varied from 0.91 to 0.99, 0.83 to 0.87, and 0.84 to 0.90 respectively. SVM showed the best specificity, but RF was the algorithm showing best AUC, sensitivity and Kappa scores.

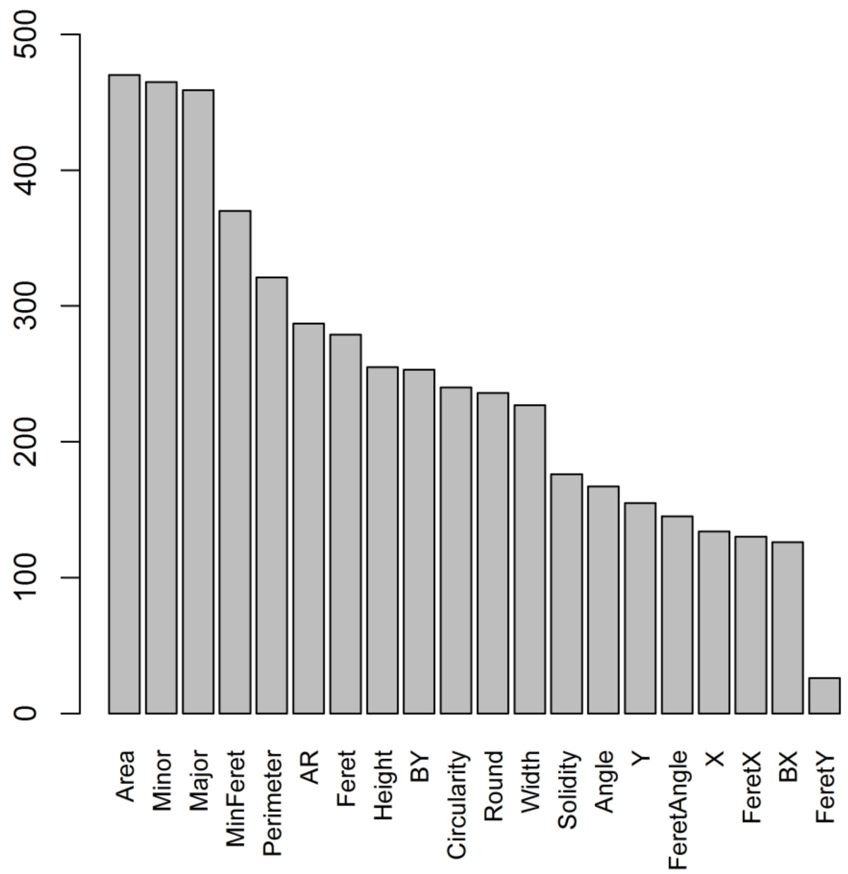

Fig 1- 4

Appearance frequency. Frequency with which the blob characteristics were selected by the different attribute selection filters during the experiment to evaluate the merits of using reduced datasets.

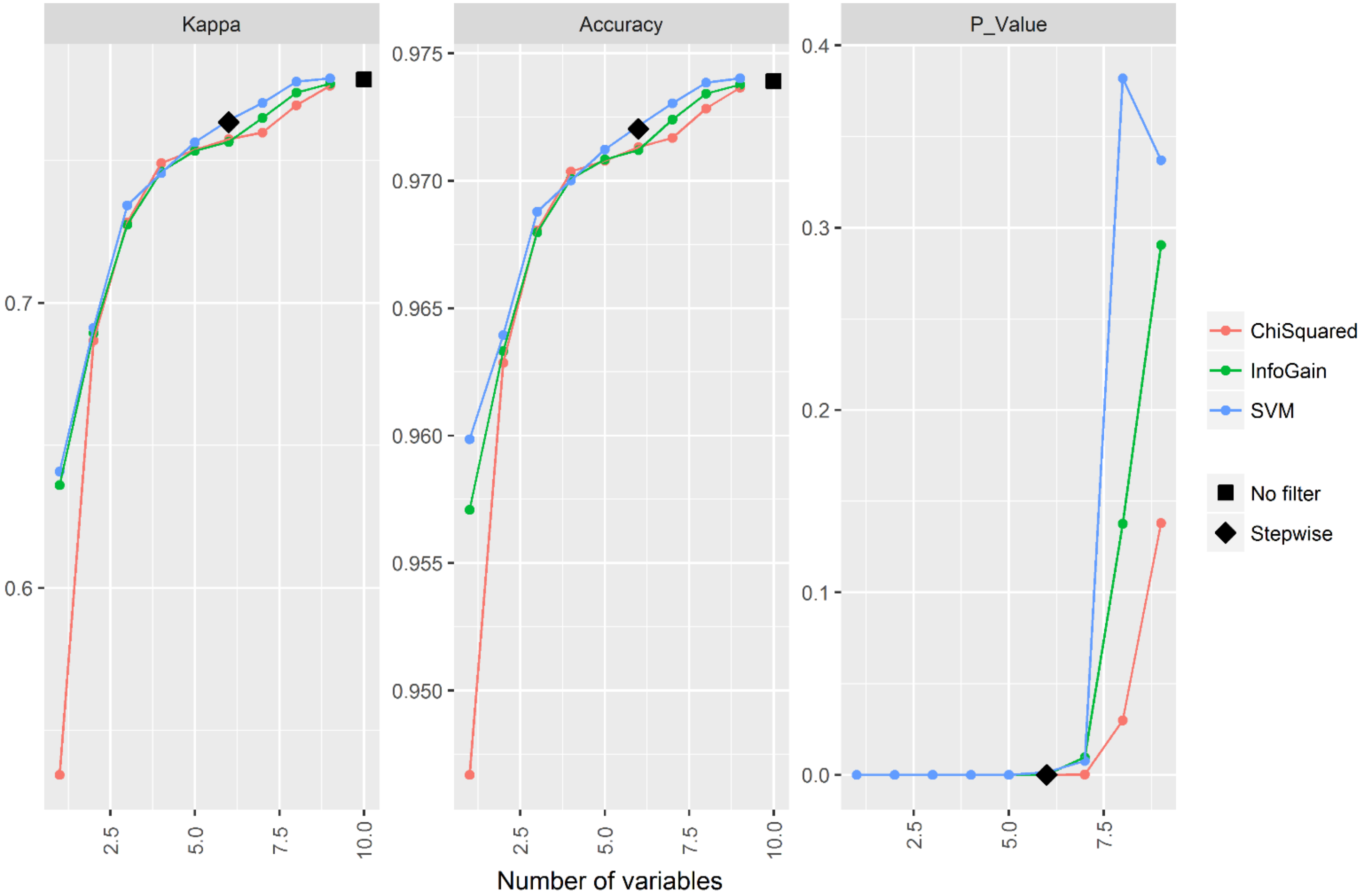

Fig 1- 5

Comparison between the complete dataset and the reduced datasets. Values for *Kappa*, *Accuracy* and *P_Value* (obtained from a corrected resampled t-test) are shown.

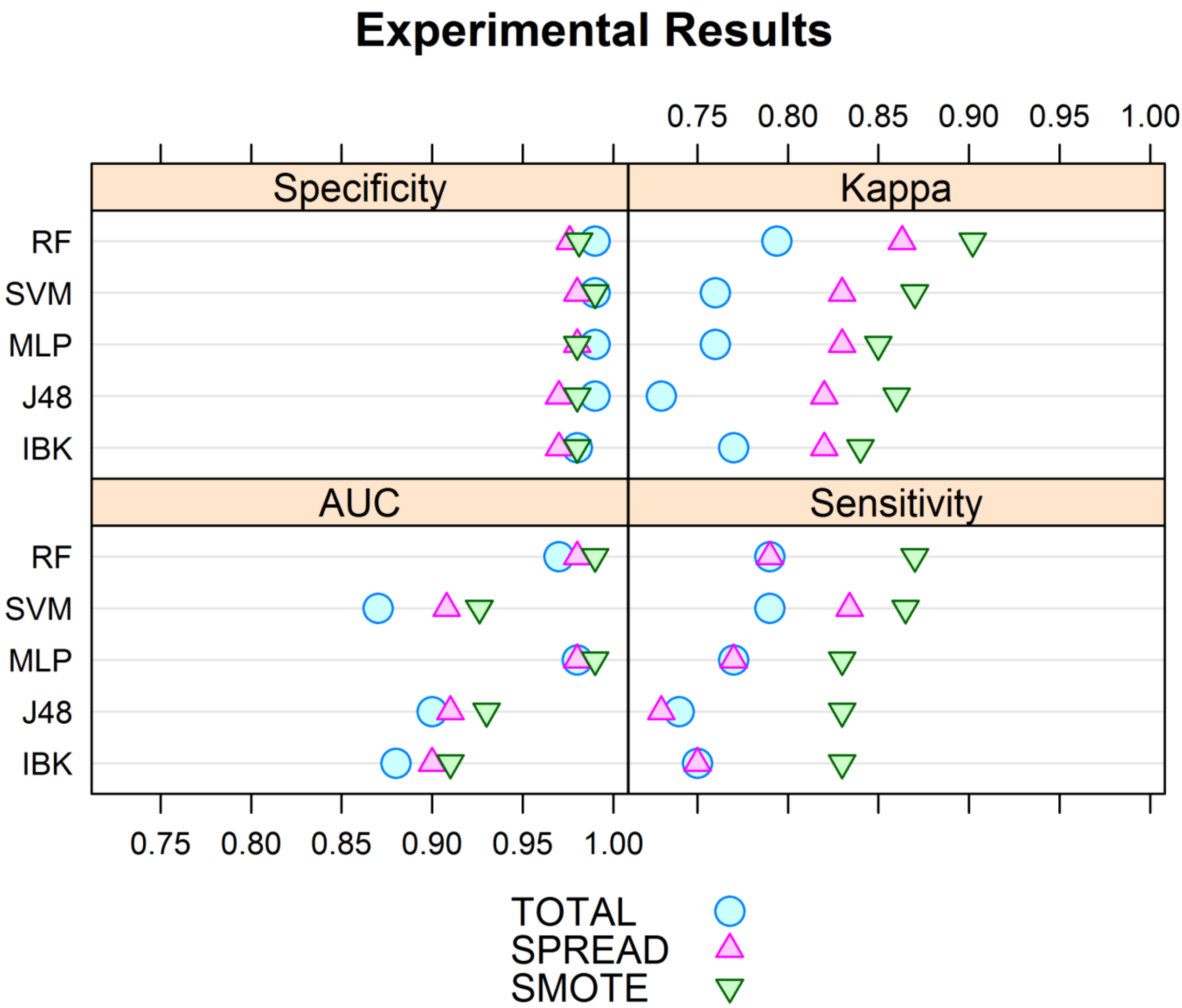

Fig 1- 6

Experiment results. Specificity, sensitivity, AUC and Kappa values for the three datasets: TOTAL, a complete dataset with 22501 instances; SPREAD, an oversampled dataset with 23998 instances; and SMOTE, a subsampled dataset with 11999 instances. The Y axis represents the classification method used: Random Forest (RF), Support Vector Machine (SVM), Multilayer Perceptron (MLP), J 48 and IBK.

1.5 Discussion

A semi-automated image processing and a supervised classification validation method have been developed and applied to detect the presence/absence of bluefin tuna in sonars that are routinely used by the fishing vessels targeting this species. The results of the classification validation tests show that all algorithms have good classification efficiency. Among the three datasets used in the experiment, the TOTAL dataset obtained a good overall performance, but balanced datasets SPREAD and SMOTE subsequently improved the general performance. The RF algorithm applied to the SMOTE dataset provided the highest accuracy among the tested algorithms. Nevertheless, although different machine learning algorithms were compared, the main objective of the experiment was not to select the best algorithm. The overall good performance in classifying "tuna" and "no tuna" cases allowed us to validate the proposed methodology. The particular algorithms can be selected on a case by case basis, considering additional constraints (e.g. computing time) in particular future applications. In fact, MLP and SVM require substantially larger calculation time, which can be an additional consideration to guide selection in specific applications such as the processing of massive amounts of data (e.g. obtained from monitoring programs in the whole fleet throughout the whole fishing season), or when the speed of the analysis is critical (e.g. for near real time monitoring of resource abundance and distribution).

On one hand, the results of this work indicate that the designed methodology has an appreciable morphologic discriminatory capacity with the processed images. On the other hand, it should be taken into account that the ratio of positives and negatives in the set of images used in this experiment may not be representative of the ratio in the commercial fishing trips conducted by the baitboat fleet in the Bay of Biscay (where a higher percentage of negative cases is expected). This will have to be taken into account when the model is applied to datasets obtained e.g. during an entire fishing campaign by estimating the real presence/absence ratios and using algorithms that properly deal with uncompensated datasets. In addition, in such an extensive application of the model, the classification will have to be semi-supervised. Although a decrease in efficiency of the classification might be expected, the generalization of the model will likely increase since a larger variety of situations will be encountered (Chapelle *et al.* 2009).

In order to enhance the strengths of this methodology, several future research lines are being developed. First, following (Brehmer *et al.* 2006), a flexible Optical Character Recognition (OCR) method to extract metadata from sonar screens (sonar signal range, tilt, gains, speed, heading, as well as additional information) is being developed so that extra information can be introduced to guide classification on an image by image basis. This will also allow providing standardized tuna school sizes, since they can be specially affected by the gain settings. And second, tools for temporal tracking of schools should be used to identify the same school in a set of sequenced images. This is a necessary step in order to be able to quantify the total number of schools observed as well as to characterize their size. Additionally, these sonar observations could be paired with additional bluefin tuna presence/absence data from logbooks and/or scientific observers, as they become available, to allow a continuous improvement of the reference dataset used to train the algorithms.

A third research line will consist in combining the MRS data with scientific echosounder data (Miquel *et al.* 2006). The main purpose of extracting the number and size of schools from MRS screenshots is to provide an index of abundance of bluefin tuna; for instance, something of the type of a sonar mapping (Smith 1970). It is clear, though, that the data obtained from MRS images might not be as precise as those from standard acoustic-trawl surveys, based on echo integration (Dragesund and Olsen 1965) of data recorded by calibrated scientific echosounders (Simmonds and MacLennan 2008). However, currently, there are no ongoing acoustic surveys estimating the abundance of Atlantic bluefin tuna in the Bay of Biscay nor anywhere else, due to the large spatial distribution and high mobility of this species. In addition, typical single-vessel acoustic-trawl surveys have spatial-temporal limitations that could be overcome by an extensive implementation of this methodology (Mayer *et al.* 2002). Taking this into account, we plan to combine the extensive sonar mapping based on this methodology with the density distribution of the schools measured by a scientific echosounder. This would allow us to overcome the inherent uncertainty of the analog sonar images and also the sampling limitation of the standard, single vessel scientific echosounder acoustics. In practical terms, the low cost of the data acquisition device and the automation of the process would allow it to be applied extensively (in many vessels and through large periods of time) while carrying scientific echosounders in one or a few of the vessels. Additionally, the side-scan sonars increase the volume sampled near the surface and thus may constitute an adequate sampler of near-surface distribution species as the bluefin tuna while feeding in the Bay of Biscay. Side scan sonars have been successfully used for fishery work in other areas in the past (Hewitt 1976; Melvin 2016; O'Driscoll and McClatchie 1998), and allow in-season decisions on the spatial and temporal sub-allocation of the total allowable catch (Melvin *et al.* 2001).

The morphological differences between the tuna and no-tuna blobs allow for their discrimination. In fact, tuna blobs were generally larger, more elongated and showed a more horizontal alignment. Some of these characteristics are ecologically meaningful, and the measurements obtained in the different blobs can inform e.g. about the size and shape of the bluefin tuna schools aggregated in the Bay of Biscay during the summer feeding season (Fig 1-7). Bauer et al (Bauer *et al.* 2015) classified the size of tuna schools based on the surface disturbance observed by airplanes. Similarly, the measurements of the area of the blobs classified as "tuna" could be used to provide estimates of the size of the different schools in the future.

The Standing Committee on Research and Statistics of ICCAT has recurrently highlighted the need for developing fishery independent indices of abundance, given the problems associated with existing CPUEs and their inability to accurately track biomass changes, especially in recent years after the implementation of the recovery plan (ICCAT 2016b). Our study can be considered a first milestone towards getting more accurate indices of abundance for juvenile bluefin tuna in the Bay of Biscay, and this can be pursued in two ways: (i) On one hand, the automated procedure presented in our study could be applied to MRS images recorded onboard commercial fishing vessels during their commercial operations. The bluefin tuna detections per unit of effort (DPUE, in number of schools per time unit) could be standardized, just in a similar way to the CPUE observations of the commercial fleet (Santiago J 2016), currently used in the bluefin tuna assessment model. The signal of inter annual variability in bluefin tuna abundance can be isolated by removing the variability in DPUE due to other variables like month, area, or skipper skill, and this time series of standardized DPUE could be used as an index of relative abundance to tune the stock assessment models. Compared to the standardized CPUE that is currently used, the standardized DPUE index would have the advantage that the detections by the sonar, unlike the catch, would be independent from factors affecting the bluefin catchability by baitboats, such as the availability of tuna forage in the environment. It would, therefore, in principle better reflect the real abundance of bluefin tuna in the Bay of Biscay, compared to the standardized CPUE that is based on what the baitboat fleet was able to finally catch. However, the variability of factors affecting detection of bluefin tuna by the sonars would need to be considered in the DPUE standardization process. Since vessels could use different sonar settings at different times, it is important to standardize DPUE observations to standard sonar range, tilt, and gain values.

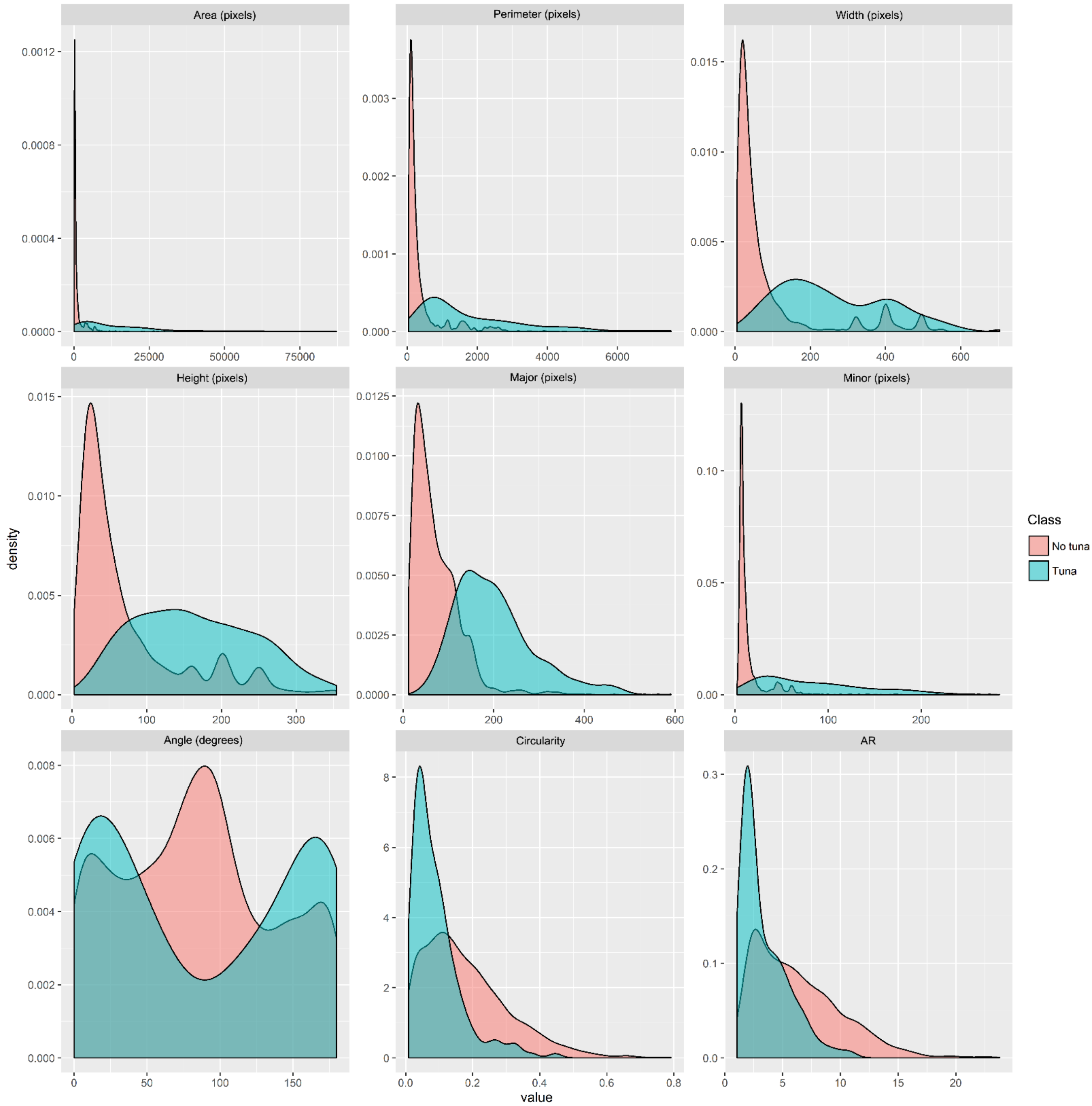

Fig 1- 7

Density plots of the measured characteristics for tuna and no-tuna blobs. Only ecologically meaningful characteristics, related to size and shape of the schools, are plotted. "Angle" refers to the angle (0-180º) between the X axis of the image and the primary axis of the best fitted ellipse to the blob contour; "circularity" is proportional to the ratio between the area and the squared perimeter, with a value of 1 representing a perfect circle and a value of 0 representing an increasingly elongated shape; Aspect Ratio (AR) is the ratio between the primary and secondary axes of the fitted ellipse., The area that a single pixel represents ranges between 0.69 m2 and 0.92 m2 (depending on the gain setting of the sonar).

(ii) On the other hand, transect based systematic surveys covering the Bay of Biscay onboard commercial baitboats equipped with MRS could be designed and conducted yearly to quantitatively estimate the bluefin tuna school density (in number of schools per area unit). Such a time series could be used as a relative index of abundance to tune stock assessment models. Given the relatively high mobility of tunas (compared to small pelagics or demersal resources), ideally the systematic surveys would involve several commercial boats equipped with MRS so that the whole area of distribution can be searched in few days. This is advantageous compared to when a single boat prospects all the area (which is often the case when scientific acoustic equipment is used to estimate total biomass), because the probabilities of immigration, emigration and double counting schools are diminished. Bluefin tuna concentrate in a relatively small area while feeding during summer in the Bay of Biscay (Fig 1-1), which provides a unique opportunity to conduct systematic abundance surveys on this widely distributed species (Arrizabalaga *et al.* 2015).

The relatively non-expensive methodology presented in this study can also be adjusted to other tuna and non-tuna pelagic fisheries by adapting the analyses to the specific type of sonar, output signal and display (see also (Brehmer *et al.* 2006)). This provides an interesting alternative to standard acoustic-trawl surveys, especially when targeting species of high mobility and/or near surface distribution. It thus provides an opportunity to use commercial fishing vessels as observatories of the pelagic ecosystem, and commercial sonars as tools to track changes in abundance of commercial species (Brehmer *et al.* 2006; Dalen and Karp 2007).

1.6 Acknowledgments

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1.7 Publication data

Type	**Peer-reviewed article**
Title	Detecting the presence-absence of bluefin tuna by automated analysis of medium-range sonars on fishing vessels
Authors	Jon Uranga[1], Haritz Arrizabalaga[1], Guillermo Boyra[1], Maria Carmen Hernandez [2, 3], Nicolas Goñi[1], Igor Arregui[1], Jose A. Fernandes[4], Yosu Yurramendi[2], Josu Santiago[1].
Affiliation	1: AZTI; Marine Research Division; Herrera Kaia z/g; 20110 Pasaia (Spain). 2: UPV/EHU, Donostia, Basque Country, Spain. 3: Centro de Investigação e de Tecnologias Agro-Ambientais e Tecnológicas (CITAB), (UTAD), Vila Real, Portugal. 4: Plymouth Marine Laboratory, Prospect Place, PL1 3DH, Plymouth, UK.
Journal	Plos ONE
Year	2017
Volume	12(2)

Argazkia: Zimarroia igotzen. Luis Barranko. 2016.

Chapter 2

Counting and sizing of bluefin tuna schools by automated analysis of sonar images and data extracted from fishing vessels

2.1 Abstract

A methodology for automated counting and sizing bluefin tuna schools using medium range sonars onboard baitboats operating in the Bay of Biscay is presented. An image analysis program, an morphometric classification model for Atlantic bluefin tuna school detection and an optical character recognition application are used to obtain morphometric data of observed bluefin tuna schools and operational data related to the baitboats and their sonar settings. With these data, a novel methodology for counting and sizing bluefin tuna schools is developed, based basically on automatic detection of bluefin tuna in consecutive sonar images and aggregation of these into unique schools. Validation of counting results is conducted by contrasting the number of estimated schools with the observed ones. The bluefin tuna school area estimates, standardized for the effects of variable sonar gain and range settings, are comparable to the real areas of the observed schools. This methodology is independent of variables, such as food availability, feeding behavior or stomach repletion, that bias the abundance index based on catch per unit of effort. Thus, an index based on sonar detections per unit of effort is proposed as an alternative. Moreover, this methodology can be implemented during systematic acoustic surveys to monitor bluefin tuna abundance in the Bay of Biscay, measured as number of tuna schools and their relative size, in a fisheries independent manner.

Keywords: Sonar, image analysis, OCR, unsupervised classification, bluefin tuna, counting and sizing, monitoring.

2.2 Introduction

The Atlantic bluefin tuna (*Thunnus thynnus*) is the largest tuna species and due to its economic value, it has been exploited for several centuries by important industrial fisheries (Fromentin and Powers 2005.) Based on the stock assessment carried out in 2006, the International Commission for the Conservation of Atlantic Tunas (ICCAT), which is responsible for the conservation of tunas in the Atlantic Ocean and its adjacent seas, established that both the eastern and western stocks, spawning in the Mediterranean and Gulf of Mexico respectively, had experienced heavy overfishing for over a decade (ICCAT 2016b) and are currently under recovery plans. The eastern stock status is uncertain (Fromentin *et al.* 2014) but new knowledge is being gathered through research programs (e.g. the Atlantic-wide Research Programme for bluefin Tuna (GBYP)), and current management follows the scientific advice).

Our study is focused at the bluefin tuna of the Bay of Biscay which is a summer feeding ground for juvenile bluefin tuna (Cort 1990). The Bay of Biscay represents a relatively small fraction of the total bluefin tuna habitat in the Atlantic (Arrizabalaga *et al.* 2015). However, it is the most important known feeding area for juveniles during their trophic migration to the Northeast Atlantic during summer (Goñi and Arrizabalaga 2010b). The study area (43-47°N and 2-6°W) is delimited by the activity of the baitboat fleet in the southeast corner of the Bay of Biscay, from June to October (Uranga *et al.* 2017). Tunas show a strong fidelity to this feeding area and tend to reside in it during the summer (Arregui I. 2015). Consequently, tuna summer fishing campaigns are strongly rooted in the Bay of Biscay since the late 1940s, when a baitboat fishery was developed (Santiago J 2016).

In tuna stock assessments, time series of standardized catch per unit effort (ICCAT 2016b) indices are used as proxies for relative abundance. The baitboat fishery in the Bay of Biscay has provided one of the longest (since 1952) abundance indices for juvenile bluefin tunas (Santiago J 2016). In fact, during decades, the standardized CPUE of the Bay of Biscay baitboat fleet has been the only abundance index available for the juvenile fraction of the entire eastern stock, and has been assumed to represent the whole (east Atlantic and Mediterranean) juvenile population trend (ICCAT 2014). However, the problems of using fishery data in this context are well known and include the lack of scientific design, correlated observations, non-random sampling or variable catchability (García *et al.* 2005). In fact, the use of standardized CPUE series as a proxy for abundance relies on the assumption of constant catchability (Mayer *et al.* 2002), while the fact is that catchability can be influenced by many circumstances, e.g.

environmental effects altering fish distribution or the detectability by fishermen, fish behaviour, changes in fishing practice, etc. Consequently, standardized CPUEs can be biased if these effects are not properly taken into account during the standardization process (Glass 2000). In the case of fisheries using baited gears such as the baitboats, catchability is directly influenced by the availability of food in the environment, feeding behavior of the fish and their stomach repletion (Antonio Di Natale M 2014; Brehmer *et al.* 2006; Stoner 2004). These variables are difficult to incorporate during the CPUE standardization process, which might lead to biased abundance indices (e.g. a large tuna biomass could yield a low baitboat CPUE in a given year if plenty of food is available in the environment and tunas are not attracted by the bait). On top of these analytical challenges, the baitboat fleet transferred their quota to other fleets operating in the Mediterranean, thus stopped their fishing operations targeting bluefin tuna during most of the 2012-2015 period. The changes in fishing practices derived by the implementation of the bluefin tuna recovery plan also affected the reliability of other abundance indices for the adult fraction of the population (ICCAT 2016a).

In this situation where the available fishery dependent indices of abundance became uncertain or were discontinued, there is a clear need to develop fishery-independent abundance indices for bluefin tuna (ICCAT 2016a). In the Bay of Biscay, acoustics were identified as the most feasible tool to develop a fishery-independent abundance index for bluefin tuna (Goñi *et al.* 2010). Acoustic systems are the most powerful scientific tools for ecosystem approach to fisheries (Koslow 2009). They have the capacity to characterize and identify targets in the water column or on the benthos for habitat mapping. Fishery acoustic techniques are well known and used routinely by fisheries scientists for biomass assessment (Foote *et al.* 2005; Simmonds and MacLennan 2008). Historically, vertically deployed echosounders were calibrated by standardized methods (Foote *et al.* 2005; Simmonds and MacLennan 2008) and used to calculate biomass of specific schools by echo integration and target strength measurement of isolated fish. Split beam echosounders were used to estimate school densities, species discrimination and individual or school dimension estimates for different species and fishing techniques (Boyra *et al.* 2013; Josse *et al.* 1999). However, these studies generally have very specific scopes and vessels have too short field ranges to tackle wide distribution areas. During the last decades studies using echosounders combined with omnidirectional sonars were conducted for several species to explore its utility for stock assessment (Misund *et al.* 1996; Misund and Coetzee 2000; Stockwell *et al.* 2012). In this sense, (Cochrane *et al.* 2003; Gerlotto *et al.* 2000; Trygonis *et al.* 2016) used omnidirectional sonars for tuna school characterization, probing their efficiency.

In the Bay of Biscay most baitboats use the commercial MAQ omnidirectional mode Medium Range Sonar (MRS) to search for tuna. These sonars are analog and non-scientific, used only for display, all the information collected being lost as soon as it is deleted from the screen. Thus, our approach is to, in collaboration with the fishing fleet, record sonar screen shots in a large number of fishing vessels during the tuna fishing campaigns or during acoustic surveys for tuna detection and design an automated methodology for analyzing these images, as a way to utilize the data currently wasted. In a previous study, (Uranga *et al.* 2017) developed a classification model that was able to detect bluefin tuna presence on sonar images. The performance of this model was considered to be very satisfactory (Kappa, sensitivity, specificity and area under the ROC indices obtained 0.87, 0.90, 0.99, 0.99 values respectively), and this development was considered to be an important milestone towards a new fisheries independent abundance index of bluefin tuna in the Bay of Biscay. However, detecting presence of bluefin tuna on sonar images that are analyzed independently is not sufficient to provide a useful index of abundance. In fact, the same tuna school is generally visualized in different sonar images, that provide repetitive measures of its size. Thus, it is necessary to link the information provided by consecutive images, so as to be able to estimate the number of tuna schools and their dimensions.

The specific objective of this paper is to validate a method for counting and sizing bluefin tuna schools in an automated way in the Bay of Biscay. This specific objective contributes to the more general objective to develop a fisheries independent index of abundance. We propose practical ways to achieve this.

2.3 Materials and Methods

The research presented in this manuscript involved no endangered nor protected species. No experimentation with animals was performed and no specific field permits were required as the scientific observations were conducted during commercial fishing activities regulated by the International Commission for the Conservation of Atlantic Tunas (ICCAT). No other ethical issues applied to the present research project.

The study area is the Bay of Biscay. The sampling strategy for an acoustic survey was defined by (Goñi N. 2016), focusing on the area of highest Bluefin tuna catches (delimited between 43-45°N and 2-3°W) according to the baitboat fleet catch records during the years

2000-2011. Within the study area, an acoustic systematic sampling survey was performed (Fig 2-1). The zig-zag transects were preferred to parallel transects because they optimize cruise time, due to the absence of inter-transects. A route with 36 waypoints was designed, to cover the whole study area by acoustic sampling during 10 consecutive days. In the present study, we analyzed a full day of continuous data recording, between waypoints 22 and 26, in order to evaluate the appropriateness of the presented methodology.

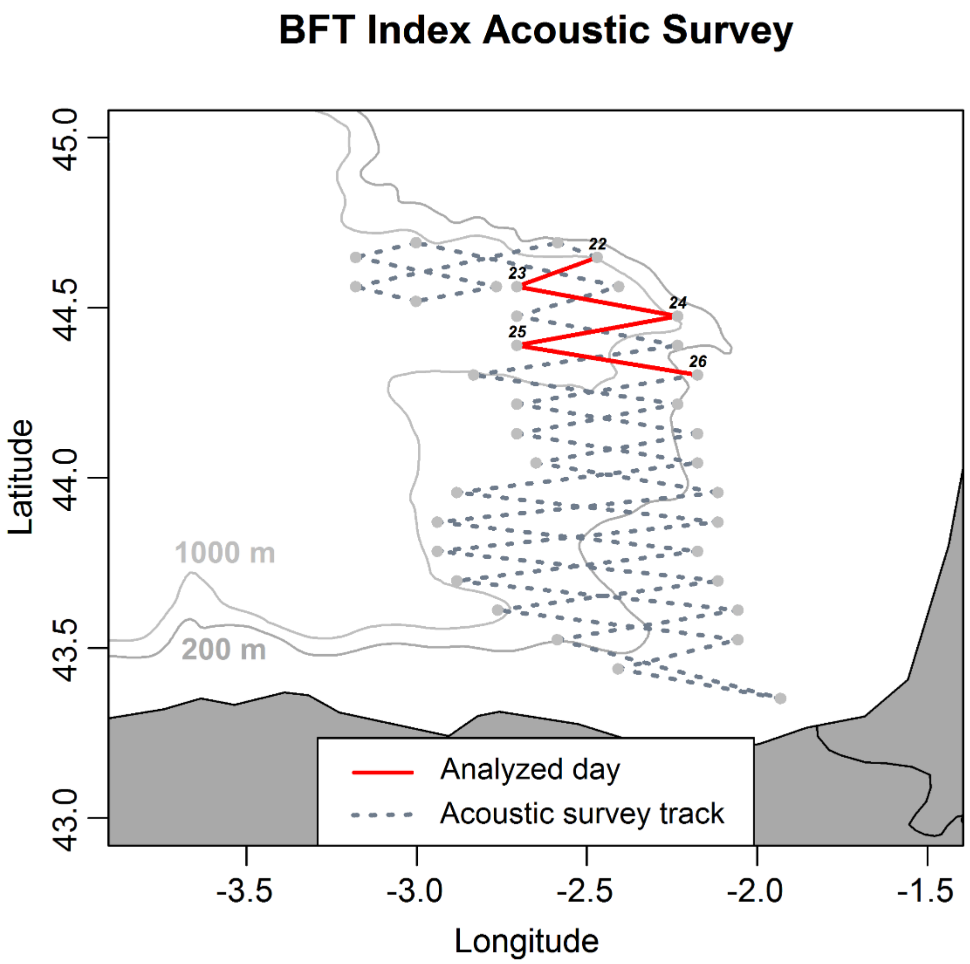


Fig 2- 1

Study area. Acoustic systematic zigzag sampling survey (Goñi N. 2016). The day analyzed in the present study is indicated by a solid line.

A reference dataset of detected schools was created by annotations taken by scientists during the survey. The main activities conducted by the scientists during the surveys were characterization of the vessel activities, accurate annotation of tuna school detections (initial and final time as well as location), recording of MAQ sonar screenshots and SIMRAD EK 60 signal, tuna tagging and biological sampling (length measurements as well as collection of tissues)(Goñi *et al.* 2010).

The images processed in this study were obtained from the commercial sonar MAQ 90 kHz. This omnidirectional MRS is used by most the Bay of Biscay baitboats. The searching range was set constant at 320 m during the whole survey with a tilt of minus 5-8° off the horizontal and vertical and horizontal beam widths of 5°. The screen dumps were acquired using an autonomous image acquisition device (Uranga *et al.* 2017).

With this data compilation, a ground truth (GT) of observed tuna schools (presence/absence) was generated and considered as the reference set of detections along the analyzed day. The bluefin tuna presence data were obtained from observations registered by the commercial sonar and/or the scientific echosounders that were annotated by scientists. The resulting positive GT for the analyzed day was composed of 34 “presence” bluefin tuna schools. Every time lapse between two consecutive presence occurrences was classified as “absence” of bluefin tuna schools. Hence, the negative GT for the analyzed day was composed of 35 bluefin tuna absence time lapses (Table 2-1).

Table 2- 1

Presence/absence cases description. Presence and absence cases during the analyzed day. The device through which the detections were recorded, the number of observed detections and their corresponding time interval (in seconds) are indicated.

Cases	Device	Nº observed detections	Time
PRESENCE	SONAR	34	6381
ABSENCE	-	35	35115

The proposed methodology to conduct the automated assessment of tuna abundance using sonar images involves two main steps: bluefin tuna school counting and bluefin tuna school sizing.

2.3.1 School counting

The process for counting bluefin tuna schools consists of several steps. The first step was to extract the morphometric characteristics of the bluefin tuna schools as proposed by (Uranga *et al.* 2017) and train the morphometric classification model (MCM). Then, the updated MCM was applied over the whole image dataset to assign the "Tuna" and "No-tuna" labels to the sub images or blobs. Once we had the tuna detections, the next step was to group them into unique schools. For this, additional data, obtained through optical character recognition (OCR) (Bunke and Wang 1997), was added to the data set. Finally, based on observed vessel behavior patterns, aggregation criteria were selected, and the counting procedure was validated performing several parameter optimization tests.

2.3.2 Morphometric Classification Model update

Sonar images were first processed by the methodology proposed by (Uranga *et al.* 2017), to obtain 20 morphometric characteristics per *blob*. The MCM used for labelling the imagery was built combining the one used by (Uranga *et al.* 2017), which contains 2795 images from 2009 and 2011 opportunistic acoustic surveys conducted in the Bay of Biscay (BoB), with additional 1273 supervised images from the 2015 acoustic survey. Using the resultant MCM and the Random Forest (RF) classification algorithm (Breiman 2001), one-day sonar imagery was labelled as "Tuna" or "No-Tuna". The studied day consists of 11.52 hours of continuous recording with a frequency of 1 screen dump per second, 41495 instances as a whole.

2.3.3 Aggregation of series of tuna detections into schools

In general, each time the vessel found a tuna school, this was recorded in several consecutive images, and thus a large amount of "tuna" labels were generated by the MCM. These contiguous "tuna" labels need to be aggregated into a single actual school that originated them using some aggregation criteria. This was guided by observed vessel behavior patterns characterized by the scientific crew during the acoustic survey of 2015 and several tuna fishing campaigns on-board fishing vessels of the BoB Basque fleet (Uranga *et al.* 2017) (shown in Table 2-2).

Operationally the skippers tend to use all the tools they have at their disposal, from tactics such as radio communication with other fishing vessels, fishermen's visual detection, seabirds tracking, etc. to more advanced technologies, such as echosounders and sonars. This is the common order of a fishing event: they usually detect the tuna school first by sonar at medium ranges; then, they head towards it, try to confirm the detection with the vertical echosounder, and in positive case, they start the fishing operation. When this happens, the mean route speed of 10 knots is rapidly reduced to 2 knots or less. This behavior can vary depending on skippers' opinion regarding the appropriateness of conducting a fishing operation or not. The duration of the stops with successful fishing is generally larger than 5 minutes.

Based on this knowledge, it was considered important to obtain time, space (geo-location) and vessel speed variables from the sonar screen dumps. Following (Brehmer *et al.* 2006), an OCR application was developed in order to automatically distinguish the different alphanumeric characters that appear at certain regions of interest on the sonar images. Several steps were undertaken during this process: selection of areas of interest within an image, preprocessing of images, segmentation of the areas of interest, extraction of characteristics, recognition of characters and validation of results. The data extracted (Fig 2-2) were: location (latitude and longitude), vessel speed, sonar beam range, gains and time. Due to observed noise in the imagery obtained, in order to clean data from outliers, OCR results were filtered by a Loess function using the R stats package (Team 2014).

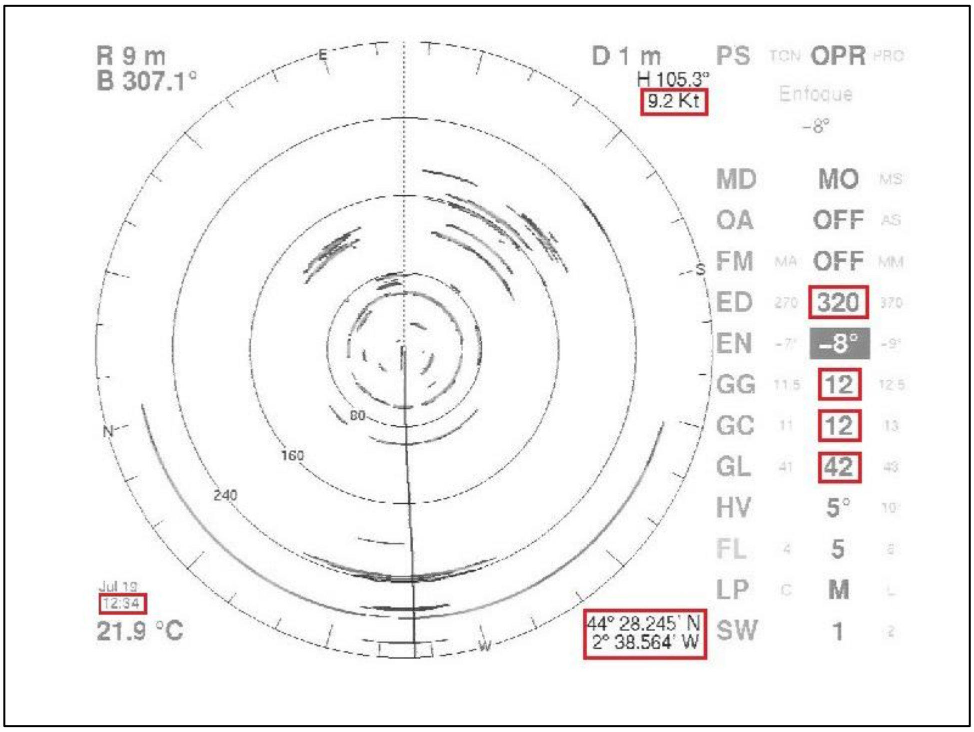


Fig 2- 2

Sample sonar binarized image. Regions of interest (ROI) are enclosed by red rectangles to show the extracted data: geographic situation (latitude and longitude), vessels speed, sonar beam range (ED) and sonar gains (GG: general gain; GC: near gain; GL: far gain).

Table 2- 2

Characterization of vessel behavior patterns. Fishing operation typology, duration and vessel speed, based on observed data from (Uranga *et al.* 2017).

Fishing operation typology	Duration (minutes)	Vessel speed (knots)
Route	-	> 9
Stop + feeding	< 5	5 - 7
Stop + fishing	> 5	3 - 5

To count the schools, a moving average (with a window of 20 seconds) was applied through the whole time-span to aggregate the series of “Tuna” labels obtained by the MCM into percentages of tuna presence within each time window. Only percentages higher than 50% were kept and the local maxima were extracted. As expected, the number of local maxima was much higher than the observed number of schools (843 local maxima against 34 observed schools). In order to aggregate these local minima into unique schools, three aggregation criteria were considered: based on time, based on spatial proximity and based on speed reductions of the vessel. Three parameter optimization tests were run in order to set optimum time, spatial proximity and vessel speed parameters to aggregate local maxima into actual tuna schools. The possible values for time and vessel speed where informed by knowledge summarized in table 2-2. For the spatial proximity criterion, we relied on previous work from (Itoh *et al.* 2012), who assumed fishing events within 2 km belonged to the same unique school. Finally, the time value ranged from 0 to 5 minutes, the spatial proximity varied from 0 to 2 km, and the vessel speed varied from 0.5 to 20 knots (Fig 2-3).

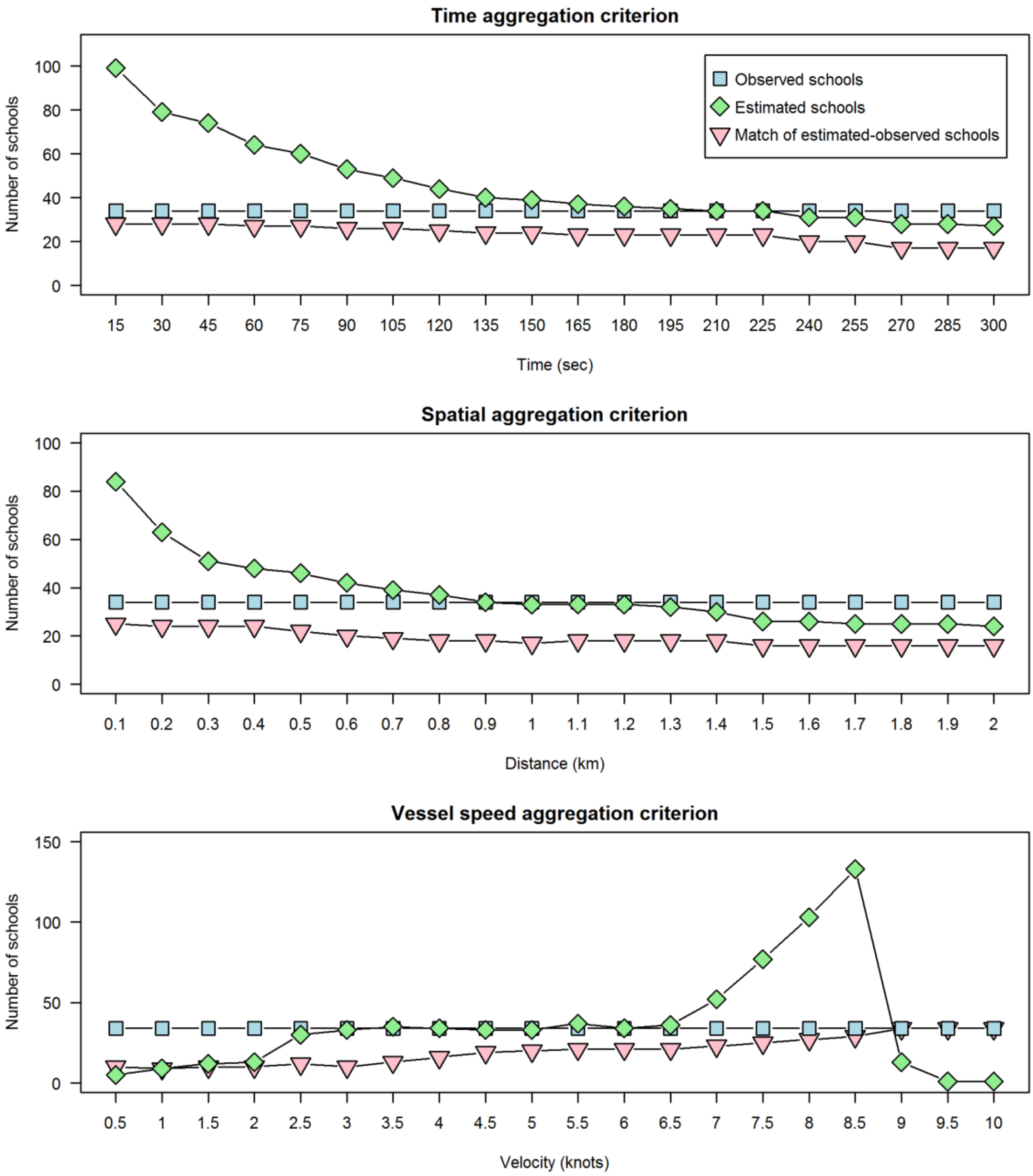


Fig 2- 3

Parameter optimization tests. In the first parameter optimization test (a), the time value ranges from 0 to 5 minutes, in 20 steps; in the second parameter optimization test (b), the spatial proximity ranges from 0 to 2 km, in 20 steps; and in the third parameter optimization test (c), the vessel speed ranges from 0 to 10 knots, in 20 steps. The observed number of schools is shown in blue; the estimated number of schools is shown in green, and the number of estimated schools matching the observed ones is shown in red.

Since the objective was to count bluefin tuna schools and calculate their size, the best performance was considered as the one that satisfied the following performance statistics:

- x (1st performance statistic): Similarity between the number of schools estimated and the number of observed schools (z) at the GT.

- y (2nd performance statistic): Similarity between the number of estimated schools that are overlapped with GT schools and the number of observed schools (z) at the GT.

These performance statistics were integrated in the following equation:

$$w = \min_{i=1\_n}\{\Delta x_i - x_{min} + \Delta y_i - y_{min}\}, \text{ given:} \qquad \text{(Eq 1)}$$

$$\Delta x_i = (x_i - z)^2$$

$$\Delta y_i = (y_i - z)^2$$

$$x_{min} = \min_{i=1\_n}\{(x_i - z_i)^2\}$$

$$y_{min} = \min_{i=1\_n}\{(y_i - z_i)^2\}$$

Where Δx_i was the squared difference between the number of schools estimated in each step (i) and the number of schools of the GT (z); Δy_i was the squared difference between the number of schools overlapping with the GT in each step (i) and the number of schools of the GT (z); x_{min} and y_{min} were the minimum squared difference between x_i and y_i, with z. The step that best fits the criteria of equation 1 is named as w. It can be noted that, in equation 1, equal weight is given to both performance statistics, x and y. The overlap between estimated schools and the GT was calculated using the IRanges R package (Lawrence M 2013). Then, the results of the three parameter optimization tests were compared to choose the best aggregating criterion.

2.3.4 Validation of the school counting results

Once the most adequate aggregating criterion and the optimum parameter values were defined, the estimated number of schools was obtained for the analyzed day. Due to the unbalanced time span between positive and negative cases (Table 2-1), the validation was performed in two different ways: by presence/absence blocks and by time (considering the time range that each block covered over the analyzed day). For each of the two ways, four different tuna aggregation options were considered: (A) based on time or space criterion; (B) based on vessel speed; based on the A | B logical condition; based on the A & B logical condition. The logical conditions were calculated using the union and intersect functions with IRanges R package (Lawrence M 2013).

In order to evaluate the eight possible results sets, their effectiveness and efficiency, we built a confusion matrix for each case. Using the confusion matrix, we evaluated the predictive accuracy of binary models on a set of predicted data for which the true observed values were known. They were composed by: the true positive rate (TP), where schools estimated as positive and overlapping with positive GT´s were considered as correct positive predictions; the true negative rate (TN), where schools estimated as negative and overlapping with the negative GT´s were considered as correct negative predictions; the false positive rate (FP), were schools estimated as positive and not overlapping with positive GT´s were considered as incorrect positive predictions; and the false negative rate (FN), where schools estimated as negative and not overlapping with negative GT´s were considered as incorrect negative predictions. Based on these parameters, the validation indices, namely sensitivity, specificity, precision and accuracy, were estimated. For all four validation indices, the best value is 1, whereas the worst is 0.

The Sensitivity (SN), also called true positive rate (TPR) or recall (REC), was calculated as the number of correct positive predictions divided by the total number of positives.

$$Sensitivity = \frac{TP}{TP+FN} \qquad \text{(Eq 2)}$$

The Specificity (SP), also called true negative rate (TNR), was calculated as the number of correct negative predictions divided by the total number of negatives.

$$Specificity = \frac{TN}{TN+FP} \qquad \text{(Eq 3)}$$

The Precision (PREC), also called positive predictive value (PPV), was calculated as the number of correct positive predictions divided by the total number of positive predictions.

$$Precision = \frac{TP}{TP+FP} \qquad \text{(Eq 4)}$$

The Accuracy (ACC) was calculated as the number of correct predictions divided by the total number of the dataset.

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \qquad \text{(Eq 5)}$$

2.4 School sizing

To provide a step forward towards estimating the abundance of tuna, a procedure was included to measure the size of the schools. The schools were directly dimensioned on the sonar screen by measuring the area of the *blobs* classified as tuna. The area estimates were corrected with a scaling factor due to the possible different ranges used by the skipper, plus a correction of the effect of the gain settings and school area dimensions.

The MAQ sonar allows three kinds of gains to be configured by the skipper: the general gain (GG) ranges from 0 to 28 and adjusts general echo response of the sonar cleaning from excessive noise; the near gain (NG) ranges from 0 to 14 and is used to avoid Surface noise; and the far gain (FG) ranges from 0 to 60 and compensates echo response attenuation in large distances due to absorption losses. As skippers set the sonar configuration following their own preferences, an image processing procedure was applied (Uranga *et al.* 2017) to set the images dimensions to the same scale, regardless of the applied gain settings.

In order to study the effect of gains on the estimated area, we set up a gain calibration experiment onboard a tuna fishing vessel (F/V *Luis Barranko*) in Hondarribia harbour, the 29th of August 2013. A rod was used to place the standard target, a tungsten carbide sphere of 38.1 mm of diameter, into the water. The target was deployed 8 m apart from the vessel and the range was confirmed at the sonar display. The tilt was set at minus 8º which is commonly used by the skippers. To allocate the target at the exact depth we seek for the maximum response of the target at the sonar display using the mean values of the GG. At this stage, images with different gain combinations were recorded: for GG, we tested a range of values from 6 (the minimum value in which the target could be observed) to 18 (above 16, noise was prevailing) in steps of 2; for NG we tested a range from 2 to 14 in steps of 2, and for FG we used steps of 30 because we observed that it had no effect at the distances we were testing. For each combination, the initial recording-time and the final recording time were annotated. Consequently, a dataset of 648 instances with the area of the target (in pixels) and gain combinations was built.

In order to infer the relationship between the gain setting and the area displayed in the sonar, the measured area was modelled as a function of GG, assuming a lognormal error distribution. Both linear and non-linear models were tested, using the Mgcv 1.7.22 package (Wood 2012) in R (Team 2014). Final model selection was based on AIC, following (Chambers and Hastie 1991). The deviance explained by the model was estimated as: 1- (residual deviance) / (null deviance)

In order to transform areas in pixels to areas in m^2, we took the sonar beam range that was set fixed at 320 m and we counted 385 pixels in the recorded sonar image. From that relationship, and assuming the pixels are square, the scaling factor of a pixel is 0.69 m^2. To obtain the areas, we multiplied the number of pixels of the area estimated by the image processing proposed by (Uranga *et al.* 2017), times the pixel scaling factor.

2.5 Results

For the time criterion, the results provided by equation 1 showed that a value of 210 seconds obtained the best performance. With this value, a total number of 34 schools were estimated, from which 23 overlapped with the GT, obtaining a positive match of 68% (Fig 2-3). The estimated optimum value for the spatial criteria was 900 meters, with which 34 schools were estimated and 18 of them overlapped with the GT getting a 53% of positive matches. Given that it performed better, we decided to use the time criteria set at 210 seconds and discard the spatial criteria to group images with tuna detections into schools. For the vessel speed criteria, based on equation 1, a value of 6 knots obtained the best results: 34 schools were estimated and 21 of them overlapped the GT, obtaining a 62 % of positive matches (Fig 2-3).

Regarding validation results for the two sets of results, per blocks and per their correspondence in time, it should be noted that in the last case results are analyzed considering the real time each block is represented, thus producing significantly different performance indices. In general, the performance statistics per time are better than per blocks, but these are not directly comparable, since they mean different things (Table 2-3). In general, results using time criteria (A) performed better than using vessel speed criteria (B), both per blocks and per time, except for precision when the evaluation was conducted per time (i.e. 0.80 for B vs 0.75 for A). Regarding results obtained by A | B and A & B, overall, the greatest improvement was obtained by A & B obtaining values of 1 for sensitivity, specificity and accuracy when evaluated per time. It is also remarkable that A | B results (i.e. precision 0.81; accuracy, 0.96) improved the precision value (0.63) of A & B and equaled the accuracy performance of B. Still, considering the four performance statistics, the best combination of values was obtained by A (per time). Per blocks, A got 23 true positive cases (the highest estimate that is equal or lower than the true number of schools, 34), overlapping with 68% of the cases from positive GT, and 100% of the negative GT (0 false negatives and 35 true negatives). For these reasons, we decided to select criteria A.

Table 2- 3

Result of the final experiment: true positive, false negative, false positive, true negative, kappa, sensitivity, specificity, accuracy and precision values are shown for each method (A: detections grouped into single schools if they are within 210 seconds; B: detections grouped into single schools if the speed is below 6 knots; A | B and A & B), per blocks and time respectively.

Per blocks	tp	fn	fp	tn	sensitivity	specificity	precision	accuracy
A	23	0	11	35	1,00	0,76	0,68	0,84
B	20	1	14	34	0,95	0,71	0,59	0,78
A | B	36	8	18	47	0,82	0,72	0,67	0,76
A & B	7	0	7	15	1,00	0,68	0,50	0,76

Per time	tp	fn	fp	tn	sensitivity	specificity	precision	accuracy
A	973	0	330	40193	1,00	0,99	0,75	0,99
B	6204	49	1512	33731	0,99	0,96	0,80	0,96
A | B	6831	220	1638	32807	0,97	0,95	0,81	0,96
A & B	346	0	204	40946	1,00	1,00	0,63	1,00

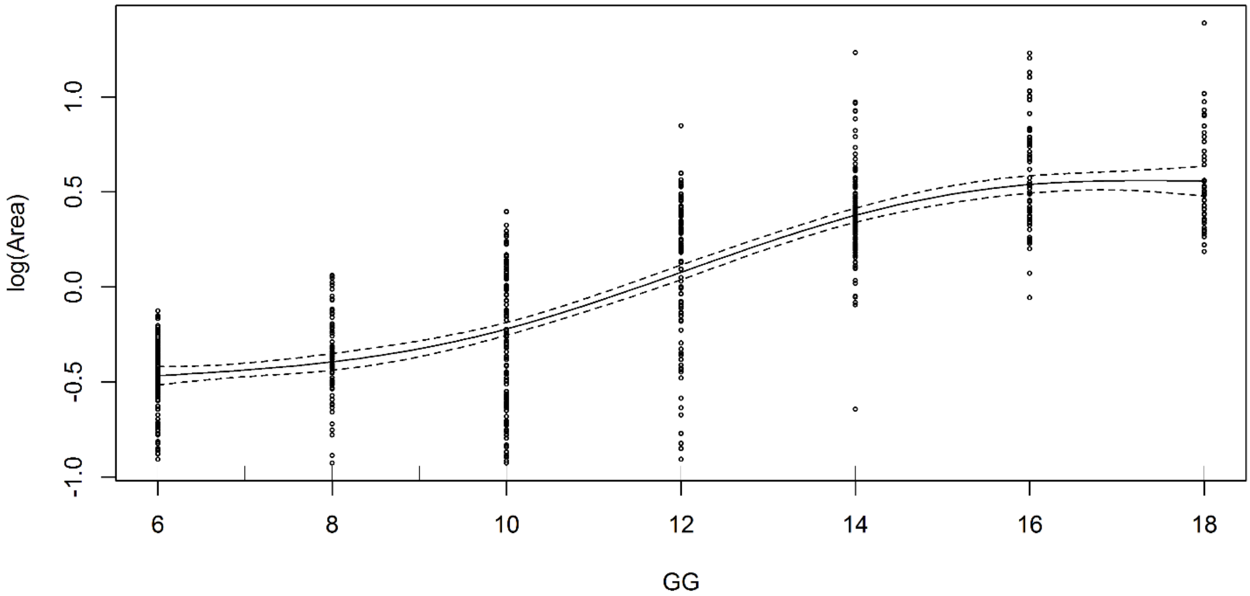


Fig 2- 4

Gain model. Response of log (Area) as a function of GG**.** The X axis represents General Gain values used at the experiment.

Regarding the area calibration experiment, due to the short distance at which the target was placed (undetectable in far distance), NG and FG settings showed no reaction to the experiment and produced non-valuable data. Regarding different GG settings, the area values showed significant variations. A nonlinear model was selected for modelling the area as a function of GG. It showed a lower AIC compared to a linear model (250.92 and 294.41, respectively) and normally distributed residuals. The area increased with the GG, but reached a plateau for GG values beyond 16, as shown in fig 2-4. The final area estimates of the bluefin tuna schools estimated with the sizing methodology ranged from 319.7 m2 to 13290 m2, with a mean of 4484 m2. Although the overall shape of the distribution of the predicted areas was similar to the one of observed areas, with the mode below 3000 m2 in both cases, the methodology slightly underestimated areas below 5000 m2 and overestimated areas between 5000 m2 and 15000 m2 (Fig 2-5).

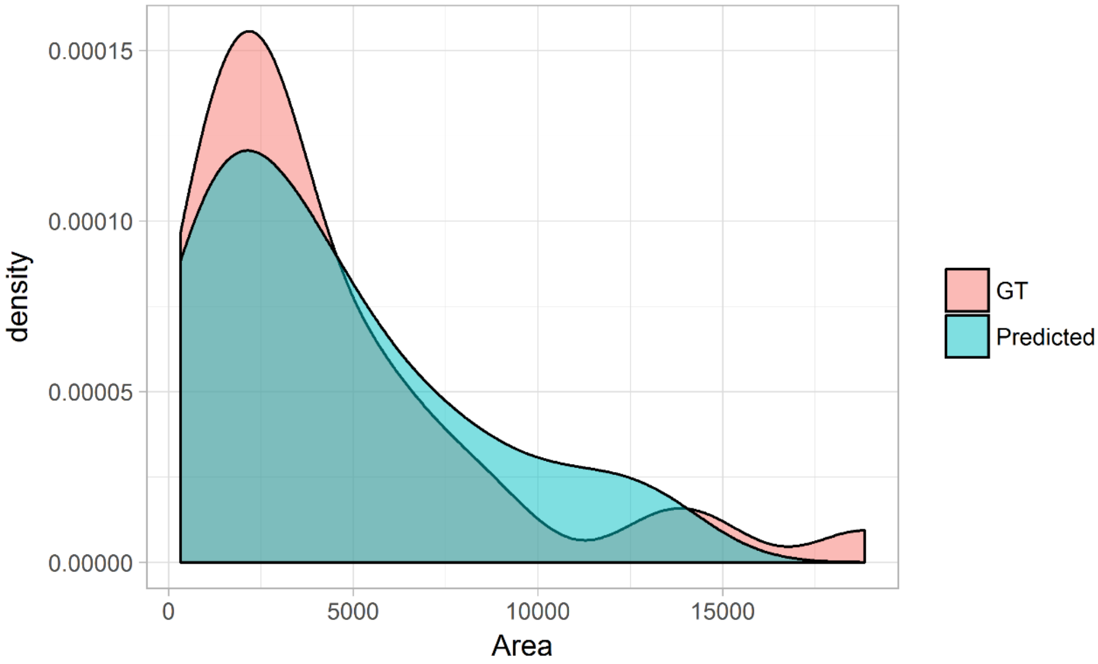


Fig 2- 5

Estimated vs observed school size distribution. Areas distribution from A results from time set and areas from the GT.

2.6 Discussion and conclusions

The previously validated MCM (Uranga *et al.* 2017) as good morphological classifier for commercial fishing campaigns of bluefin tuna in the BoB have been updated with new images from a scientific acoustic systematic sampling survey and applied to detect bluefin tuna schools. The obtained counting results demonstrated that the methodology can integrate data from a variety of surveys during multiple years, and it can be used to detect bluefin tuna schools for different data sources. MCM from 2009-2011 (Uranga *et al.* 2017) was built on data where the ratio between presence and absence images was of 1/14.03 while in the current approach we had a 1/43 ratio. Due to the greater unbalance between positive and negative observations, as well as the addition of extra variability in the reference set (potentially including other species such as albacore, anchovy or cetaceans, non-controlled noise, etc.), a decrease in efficiency was expected, but the good performance of the non-supervised classification (Chapelle *et al.* 2009) motivates the exploration of new unsupervised approaches over extensive sonar imagery in the future, In this sense, the wider the application of this methodology, the larger the number of images to be processed, so further research on efficient image processing methods are encouraged.

The sonar images were obtained thanks to the collaboration of the fishing community and the “black box” mode in which the acquisition device was designed. Key information to develop the counting and sizing methodology, such as geolocation, speed and sonar setup (range and gain) can be extracted by OCR using the imagery itself and avoiding the need of auxiliary data acquisition devices (e.g. GPS) or extra people onboard. This fact plays an important role when data acquisition is carried out during fishing operations where any disruption affecting skippers fishing operations routine can affect the data exchange between fishermen and scientists. It should be highlighted the importance of strengthening the relationship between scientific and fisheries communities in order to extend faithful collaborations.

Regarding the utility of the data extracted by OCR, vessel speed, for example, did not stand out as the best aggregation criterion at the performed parameter optimization tests. Nevertheless, it could be useful for future studies were both, data extracted by OCR and labels obtained by the MCM, could work together towards improved methodologies for detecting tuna schools. In addition, spatial coordinates are essential for spatial representations and future geostatistical work (Doray *et al.* 2008), and range and gain values are essential to standardize the school dimensions. Thus, the OCR application developed is considered an essential part of the counting and sizing approach.

When aggregating the series of tuna detections into schools, the estimated optimum parameter values were similar to the values observed during scientific and commercial fishing campaigns. In this regard, it is believed that our methodology represents correctly the baitboat fishing activity targeting bluefin tuna and thus it is appropriate for bluefin tuna school counting. The best validation results were obtained when using time criteria (A) to group tuna detections into schools. However, there is not a big gap between time vs vessel speed (B) criteria and further studies may examine how they could complement each other to improve the detection ratios. In general, our counting approach yielded very high sensitivity and accuracy scores. The case A, the one that best performed, predicted the exact number of schools (34), and 23 of them where within the 34 reference set of schools. This highlights the need to continue improving the methodology and decrease the number of FP cases. Doing so would decrease the differences between observed and predicted school size distributions even more.

For automatic detection and counting of bluefin schools we have set optimum parameter values (i.e. 210 seconds) to group detections into single schools. However, in some circumstances (e.g. during postprocessing of acoustic surveys) it might not be necessary nor ideal to stick to this value. Instead, analysts might want to consider other alternatives. Still, the classifying the images in an automatic way using the MCM model might help focus on the areas where the probability to find tuna schools is higher, thus saving considerable time and effort during post-processing of data collected during acoustic surveys.

Using combined criteria provided estimates of number of schools far from the number of schools observed at the GT. With A | B, as many as 54 schools were estimated and with A & B, only 14. The idea of combining A and B criteria was to test whether the information from the vessel behavior could improve the detection made only based on the MCM. The A | B criteria was intended as a greedier condition for estimating numbers of schools in the hope that it may not miss a school. And the A & B criteria as a more conservative one, i.e., the one that, by checking two conditions, may never point to a wrong school. In this sense, A | B was successful, because all the schools in the GT were detected (plus several other false positives). This could be useful in the future as a pre-filtering step before expert validation.

In order to understand the improvements of the performance statistics when the analysis is conducted per time (compared to per blocks), it must be borne in mind that the confusion matrices are modified since, essentially, the number of observations in the GT is different, affecting the proportions of TP, FP, TN and FN. In addition, the number of instances was much larger (Table 2-3) in the time set (41496) than in the blocks set (69), leading to a general improvement of performance statistics. Moreover, the mean time ranges for positive cases in A & B were shorter (132 seconds) than negative ones (1057 seconds), and this improved the specificity, precision and accuracy scores. Also, between A and B it was observed that time ranges in B were larger than in A and this affected the number of FPs and thereby to the increase of precision.

Regarding the area estimations shown at fig 2-5, it is observed that the estimated areas and the GT areas are quite similar. Thus, it can be concluded that our approach was able to exactly match the real number of bluefin schools and provide a reasonably good characterization of their size. Obtained areas are given in m^2, they are scaled based on the sonar display range and corrected according to the gain model (Fig 2-4). Estimates from commercial MRS imagery are probably not as precise as those from standard acoustic-trawl surveys, which are echo integrated (Dragesund and Olsen 1965) and are recorded by calibrated scientific echo sounders (Simmonds and MacLennan 2008). Thus, looking ahead, area estimates obtained by MRS can be used to estimate 2D horizontal relative size of schools and in order to improve accuracy of school size and posterior biomass estimates, they could be combined with scientific echosounder data (Miquel *et al.* 2006). Also side scan sonars, which increase the volume sampled near the surface and have been used for assessment of fishery resources in other areas (Hewitt 1976; Melvin 2016; O'Driscoll and McClatchie 1998) can be adequate samplers for the bluefin tuna while feeding in the Bay of Biscay. Due to the large spatial distribution areas and high mobility of this species, no acoustic surveys were performed during the last decades for the bluefin tuna in the Eastern Atlantic. But since 2015, a systematic acoustic survey to count bluefin tuna schools and estimate their size using MRS and scientific acoustic devices is being conducted in the Bay of Biscay (Goñi N. 2016). This kind of surveys are valuable to start building an inter-annual series of number of schools and to investigate the density distribution of the schools measured by scientific echosounder. To cover the whole distribution area we plan an extensive implementation of this methodology (Mayer *et al.* 2002). Thanks to the low cost of the automated data acquisition device and the collaboration of the Basque tuna fishing fleet, we can apply our methodology in several baitboats throughout the summer tuna fishing campaigns, from June to October. The automatic analysis of the data collected during such fishing campaigns or acoustic scientific surveys, would allow to map the schools and their size as shown in fig 2-6. In this representation of the spatial distribution of the schools of the GT and the estimated schools after applying the methodology developed in this study (based on time criteria, A) we can see that although we can have a generally realistic distribution of the school spatial distribution, there are some areas (e.g. most northern areas) with bluefin schools that go undetected. Likewise, the size of the largest school seems to be underestimated. Future improvements of this methodology might allow to have more precision on the exact location and size of every school.

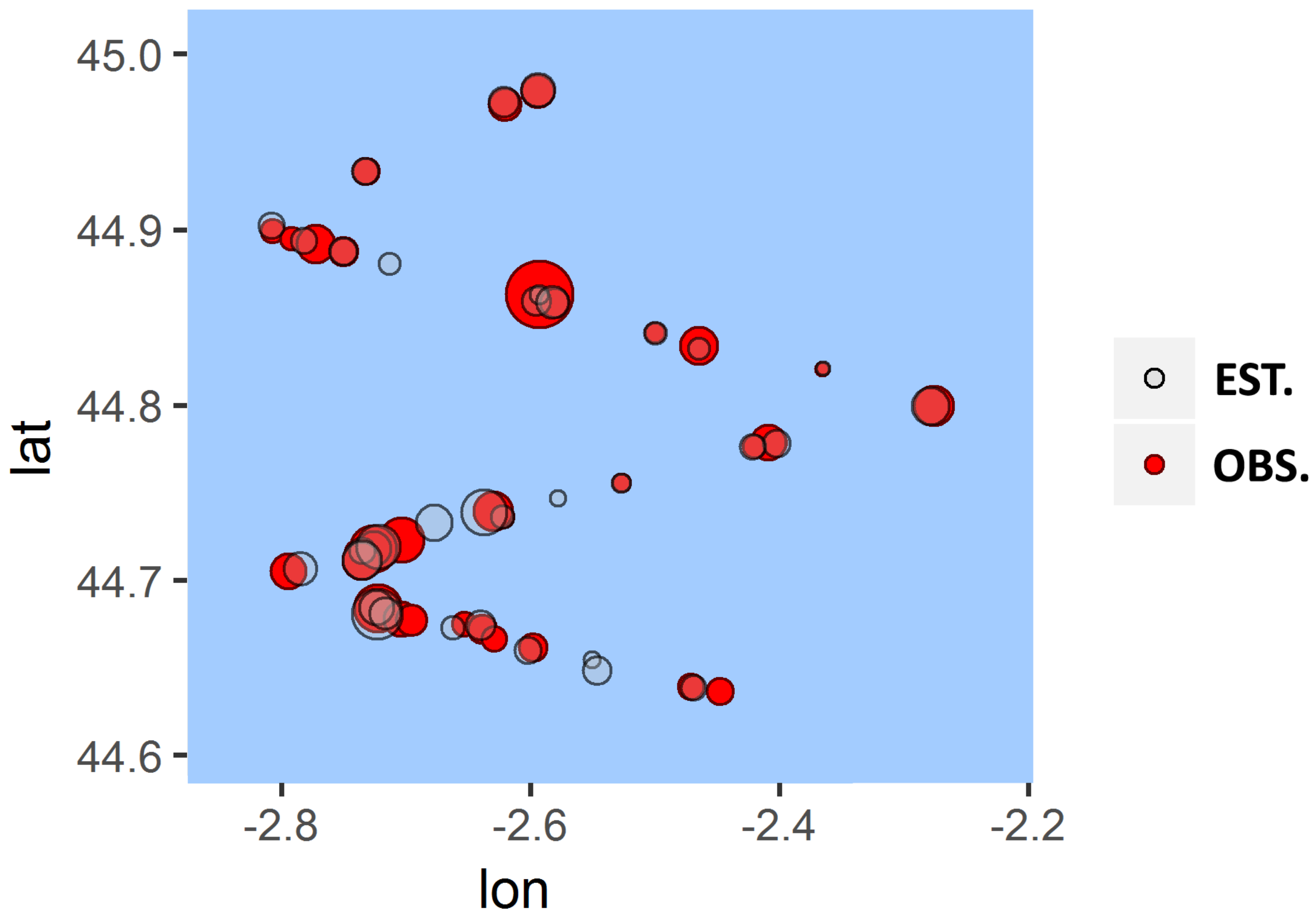


Fig 2- 6

Spatial representation. Estimated schools and observed schools (GT). The schools were estimated aggregating detections according to the time criteria. The represented size of the schools is proportional to the estimated size.

Development of fishery independent abundance indices is a strongly pursued goal for the Standing Committee on Research and Statistics of ICCAT. Latest CPUE evaluations underlined the difficulties to accurately track biomass changes (ICCAT 2016b). In this sense, our study is aligned with this objective and it is being applied to two research lines.

The first one is focused on the monitoring of commercial fishing activities. The automated acquisition methodology presented in this study is being installed onboard commercial fishing vessels to continuously record their commercial operations. The procedure presented in our study will be further tested by pairing results with annotations taken by scientific observers boarded on fishing vessel thanks to collaboration of the Basque fleet. All the counting results collected would constitute the input data to generate a new bluefin tuna detection per unit of effort (DPUE) index, in number of schools detected per time unit, for their use as inputs in bluefin tuna stock assessment models. This standardized DPUE index would be independent from factors affecting bluefin tuna catchability (and thus the CPUE index), like food availability, feeding behavior and stomach repletion (Arreguín-Sánchez 1996; Stoner 2004). On the other hand, factors concerning detection of bluefin tuna by the sonars would need to be considered in the DPUE standardization process, that could be conducted using methodologies similar to the ones used for standardizing CPUE observations (Santiago J 2016). Our proposed methodology already considers a way to standardize school size for different sonar settings (such as range scale and gain) used by different vessels/skippers at different times. However, the detectability of tuna schools might be affected by these and other variables (e.g. time, area, weather conditions) that need to be considered.

The second research line is focused on systematic scientific surveys covering the Bay of Biscay onboard commercial baitboats equipped with MRS with predefined sonar settings. The analysis on the survey data presented in this study is the first step for establishing annual surveys to quantitatively estimate the bluefin tuna school density (in number of schools per area unit). Time series of registered schools could be used as a relative index of abundance to feed bluefin tuna stock assessment models. Thanks to the high fidelity of tuna in Bay of Biscay and that they generally concentrate in a relatively small area while feeding during summer in the Bay of Biscay (Arrizabalaga *et al.* 2015) we have a privileged opportunity for conducting systematic abundance surveys on this otherwise widely distributed species.

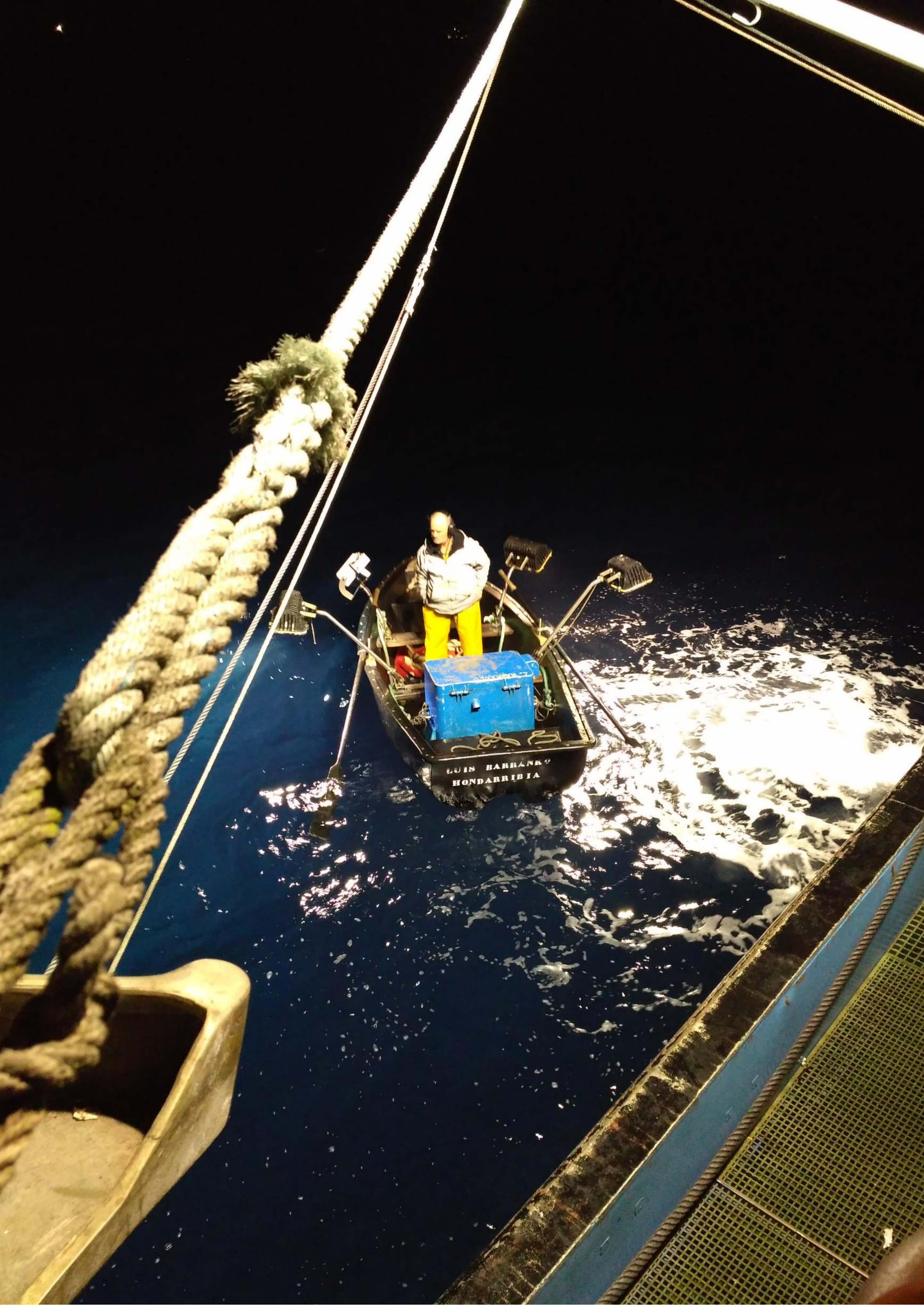
In conclusion, we present a new way to observe bluefin tuna in the Bay of Biscay based on sonar imagery. Counting and sizing results presented are proving the capability of the methodology to be applied both during commercial operations and systematic acoustic surveys. The use of commercial sonars as observatories of the pelagic ecosystem, in combination with new methodologies based on image processing and data-mining algorithms have shown their potential to work towards fisheries independent techniques and with the final aim of improving the current evaluation methods for bluefin tuna abundance. Furthermore, the adaptability shown by the methodology makes it suitable to extrapolate its application to other tuna (including tropical) and non-tuna pelagic fisheries, and to different acoustic devices (Brehmer *et al.* 2006).

2.7 Aknowledgements

We thank the skippers and crews of the F/V Txingudi for their cooperation during the scientific surveys. We thank also the skippers and crews of the F/V Luis Barranko for their collaboration regarding MRS sonar data exchange and for accepting the presence of a scientific observer during several fishing trips to perform ABT fishing operation observations

2.8 Publication data

Type	**Peer-reviewed article (Submitted)**
Title	Counting and sizing of bluefin tuna schools by automated analysis of sonar images and data extracted from fishing vessels
Authors	Jon Uranga[1], Haritz Arrizabalaga[1], Guillermo Boyra[1], Maria Carmen Hernandez [2, 3], Nicolas Goñi1
Affiliation	1: AZTI; Marine Research Division; Herrera Kaia z/g; 20110 Pasaia (Spain). 2: UPV/EHU, Donostia, Basque Country, Spain 3: Centro de Investigação e de Tecnologias Agro-Ambientais e Tecnológicas (CITAB), (UTAD), Vila Real, Portugal
Journal	Plos ONE
Year	2017


LUIS BARRANKO
HONDARRIBIA

Argazkia: Beita egiteko prestatzen. Barranko. 2016.

General discussion

New knowledge, methodology and original applications developed at the present research work are presented with the aim of addressing the challenge of estimating bluefin tuna abundance in the Bay of Biscay using fishery independent methods. Keeping in mind progress and limitations cited at the state of the art in fisheries acoustics and artificial intelligence fields in relation to ABT and after the development of the present work, the following final reflections emerge.

The way in which sonar imagery onboard fishing vessels is acquired is a key step because if it is not correctly done, sonar imagery can be lost or incorrectly registered, and all the subsequent steps of the presented study are not applicable. In this respect, the design of a device that guarantees the continuous recording without external human control is necessary. The system we designed works as a “black box” and controls a series of possible issues, such as planned or accidental cuts of electric power caused by vessel maintenance or other external causes. In these cases, the image acquisition device has been configured to restart automatically so as to avoid major data loses. Moreover, a Java executable program is automatically launched to record images and control its correct evolution. A safe location for the recording system is also important in order to protect the device from external climatic conditions or inadequate manipulation by onboard crew. In conclusion, the acquisition device that we use (Uranga *et al.* 2017) records images correctly in an autonomous way, controls several issues and does not disturb fishing operations at any moment, which is an important requirement set by skippers in general.

Based on the results shown in chapters 1 and 2, the generic image analysis program developed shows potential to correctly process images recorded by MRS and to use the extracted features to detect ABT presence and absence throughout the sonar imagery. Optimized programs would allow to shorten processing times, and this would represent a more useful tool to analyse future MRS data. The processing program could also be displayed in a more “user-friendly” mode to allow introducing, on a case by case basis, the specific sonar characteristics of interest (model, image size, regions of interest, filtering options, etc.). This would enhance the feasibility to adapt the current work to other sonars used in other fisheries or other data sources in general.

Image analysis methodology is related to data volume issues originated from the large number of images subject to be pre-processed as first instance, and from sub-images generated by the image processing programs at the segmentation step. With the first image processing program three to four days were necessary to process one day imagery and this was the main reason for analysing a single day imagery in the 2nd chapter of this thesis. In order to lighten the segmentation tasks from which morphometric characteristics are generated, *blobs* smaller than 100 pixels were removed to filter the noise, thus only larger *blob*s were considered tuna candidates and were subject to a characteristics extraction process. Currently, the image processing program has been optimized and we can process one day imagery in less than a day, so in the near future this methodology could be applied to data recorded over the whole acoustic survey or the whole tuna fishing campaign, allowing the initiation of new abundance indices of ABT in the BoB.

The analytical power of data mining tools allowed to evaluate different filters to equilibrate unbalanced databases, alternative attribute selection algorithms to select the set of morphometric characteristics that best discriminate tuna schools, and competing classification algorithms to identify tuna morphologically in sonar imagery. In chapter 1, it was concluded that using all available (twenty) morphometric characteristics, an oversampling filter (SMOTE) and the Random Forest classification algorithm was the best choice to detect ABT in MRS imagery. These tools have given correct solution to our necessities but other additional options are not discarded and can be considered in different future applications. New techniques and algorithms to improve the potential of current classification algorithms could we explored. Deep Learning algorithms (Abadi *et al.* 2016) have shown to perform very well at computer vision, image processing, audio processing, etc. so it could be an interesting research line to consider.

The classification power of the MCM developed in this study has shown to be very efficient over ABT images in the BoB. Indeed, the good performance indicators obtained when detecting ABT schools in MRS imagery leads us to consider its potential applicability in sonar imagery of other bluefin tuna fisheries, as well as other pelagic tuna and non-tuna fisheries by adapting the analyses to the specific type of sonar used.

The Basque baitboat fleet also targets albacore tuna (*Thunnus alalunga*) in the BoB and adjacent waters, using the same MRS sonars. Thus, classification of this species is considered to be affordable. The MCM would need to be refitted and the optimum parameter values to count tuna schools re-estimated, but no other major adjustments are envisaged. Compared to ABFT residing mostly within the BoB, albacore tuna shows a larger spatial distribution in offshore areas of the northeast Atlantic. Although the position of the catch would already be a very good proxy for species identification, both species have an overlap area. Thus, it would be useful to be able to automatically discriminate between these two, and ideally other (e.g.

anchovy) pelagic species that share the habitat. This multispecies identification represents a new, challenging research line that might request including additional characteristics in the classification models. Based on two fishing trips conducted during summer 2016, it was observed that albacore tuna revealed a light red tone surrounded by a fine green borderline while ABT showed a strong red response. The strongest acoustic response is observed for the adult ABT schools, that seem to be easiest to discriminate on MRS images. But some small juvenile ABFT schools can be confounded with large albacore tuna. Thus, although the species discrimination is not straightforward, including colour characteristics when training supervised datasets to generate new MCM may allow to distinguish different tuna species. Thus, for further upcoming classification challenges, a multi-species supervised data experiment must be performed, where ABT, albacore tuna, anchovy and BoB typical noise would be the possible cases. Supervised images for all of them have been gathered during the last years, so the species discriminatory capacity of current and/or improved methodologies can be checked.

Regarding the capacity to analyze most commercially exploited tropical tuna species such as yellowfin tuna (*Thunnus albacares*), bigeye (*Thunnus obesus*) and skipjack (*Katsuwonus pelamis*), some issues should be considered. Two different fishing modes are used in the tropical tuna purse seine fishery: fishing operations on free swimming schools and fishing operations on FADs (Fish Aggregating Devices). Most purse seiners are equipped with modern long-range sonars that are used to detect and follow tuna schools during free school fishing operations. The frequency of these sonars is similar to the MRS studied on this thesis, and the echogram displayed at the screens of these purse seiners also shows similarities to those of MRS, which can ease the adaptation of our methodology to this fishing mode. On the other hand, acoustic data provided by echosounders deployed at FADs derive from different frequency sonars which, moreover, apply temporal filters before transmission to limit energy consumption. These factors produce lower quality acoustic data and applicability to this kind of data is supposed to be more challenging.

To be able to address the tuna counting and sizing problem in an unsupervised way, apart from “tuna” and “no-tuna” labels provided by the MCM, extra data related to the vessel (speed, location, gain, range, etc.) is necessary and therefore the OCR application is used to automatically distinguish the different alphanumeric characters that appear at certain regions of interest throughout the sonar images (Uranga 2013). The OCR application involves several steps: selection of areas of interest where parameters subject to be useful are located are defined, preprocessing of images, segmentation of the areas of interest, extraction of characteristics, recognition of characters and validation of results. The OCR application can extract characters from any region of interest in the image and the training dataset could be adapted to any kind of sonar image. This means that this application could be adapted to extract data from other acoustic devices or to analyze images from other fisheries.

According to area estimates presented in chapter 2, it is observed that the estimated areas are similar to those of the GT. This shows that when processing MRS images with our methodology, a good characterization of the school size can be obtained. However, taking into account that MRS are not scientific sonars and thus are less accurate, the estimated areas can be used mainly to characterize the 2D shape of ABT schools. Another future research line consists in combining the MRS data with scientific echosounder or sonar data. This way, we would sum the capacity of the present methodology to analyze large areas with the accuracy improvements regarding schools size, density and distribution provided by scientific echosounders or horizontally deployed scientific sonars.

To validate our results in chapters 1 and 2, we used observed tuna schools annotated by scientific observers who used a new standardized template to record bluefin tuna presence. These annotations constitute the reference dataset of observed bluefin tuna schools and serve for selecting tuna sonar images both for supervised classification and for validation of counting and sizing methodology. The final aim of the templates is to record all tuna detections and all their initial and final time as accurately as possible. Although the methodology developed here is autonomous, in the sense that no auxiliary data sources (logbooks, observers, etc.) are needed for it to be applied, the reference datasets generated this way can continue to be fed by additional scientific observations in the future. This enlarged reference dataset will allow to improve the methodology developed in this study.

In conclusion, the automated analysis of MRS imagery based in the present methodology allows to detect, count and size ABT schools in the BoB. This can help address current challenges to obtain accurate abundance indices for ABT in the BoB. A series of acoustic detections per unit effort (DPUE) could represent a good alternative to the currently used catch per unit effort (CPUE), since the latter might be biased due to food availability, stomach repletion or feeding behavior. Currently we have just started to collect data and we have just established the methodologic basis for an extensive application. To obtain meaningful results we must keep on acquiring and processing sonar data continuously along several years with the objective of composing a meaningful DPUE series of data.

On the other hand, fisheries independent indices of abundance can also be generated using this methodology. Beyond its use in 2015 by Goñi et al. (2016), where one vessels covered the study area in about 10 days, an acoustic surveys research with two research vessels was also performed by by Monstad et al. (1992) on blue whiting (*Micromesistius poutassou*) in the spawning area. For future surveys at the BoB, the fact that most of the fleet uses the MAQ MRS allows to additional survey configurations using several boats at a time, allowing to cover the area very quickly (e.g. in two days using 5 boats). This might also allow to conduct several surveys along the summer (e.g. one per month), instead of just one in selected dates, to account for temporal variability in ABFT presence and detectability in the BoB.

Argazkia: Begizko atun behaketa. Barranko.2016.

Conclusions

Using methodologies and applications described at chapter 1 and chapter 2, raw medium range sonar imagery is recorded onboard fishing vessels and processed to detect, count and size tuna schools. The specific results obtained on this thesis dissertation allowed to validate the following hypothesis:

"Automated analysis of raw medium range sonar imagery recorded onboard fishing vessels allows to automatically detect, count and size bluefin tuna schools in commercial tuna fishing campaigns and scientific acoustic surveys, as a way to improve resource monitoring, scientific advice and ultimately, fishery management of this important resource"

The following is a series of conclusions directly related to each of the stages followed in the development of the methodologies and applications presented in this document.

Regarding detection of the presence-absence of bluefin tuna at MRS imagery recorded on fishing vessels:

- Electronic data acquisition from the Basque fishing fleet is possible due to the collaboration between scientists and fishermen. The data acquisition devise is designed to act as a "black box" that avoids compromising the activity of fishermen during regular operations. This point helps fishermen to collaborate, share their expertise and allow to extract data from their acoustic devices in an extensive way.
- The semi-automated image processing application applied to the MRS imagery, provides characteristics of *blobs*, producing useful labelled databases prior to the morphologic supervised classification step.
- In the comparative study performed between balanced datasets (applying oversampling and subsampling techniques) and original unbalanced dataset we obtain higher accuracy using oversampling techniques (SMOTE). This reflects that the use of filters is justified in databases derived from tuna presence/absence sonar imagery analysis.
- The supervised classification results obtained using attribute selection algorithms suggest that no subset of characteristics can improve the classification results of the principal dataset with the whole set of 20 morphological characteristics.

- Morphological features assigned to tuna and no-tuna blobs after the supervised classification show differences. Tuna blobs are generally larger, more elongated and show a more horizontal alignment.
- The comparative study among five classification algorithms and three databases show that the best performance is obtained by the Random forest algorithm.
- The methodology can integrate new data from a variety of sources (commercial fishing campaigns and scientific acoustic systematic sampling surveys) and it can be used to detect bluefin tuna schools in both data sources.

Regarding counting and dimensioning bluefin tuna schools:

- Key information to develop the counting and sizing methodology, such as geolocation, speed and sonar setup (range and gain) can be extracted by OCR using the imagery itself and avoiding the need of auxiliary data acquisition devices (e.g. GPS). This fact plays an important role when data acquisition is carried out during fishing operations where any disruption affecting skippers fishing operation routine can affect the data exchange between fishermen and scientists.
- A good characterization of fishing operations through scientific observers is important so as to guide and validate the results. The aggregation criteria provided by the parameter optimization tests and used at the tuna school counting process were similar to those characterized by observers during scientific and commercial fishing campaigns. Consequently, the methodology represents correctly the baitboat fishing activity and thus it is appropriate for ABT school counting.
- Applying our method, the exact number of schools (34) are predicted and 23 of them are within the 34 reference set of schools. This should be further investigated in future with the aim of improving the methodology and decrease the number of FP cases.
- Counting results demonstrate that the presented methodology performs well with hardly unbalanced databases (1/43 ratio between presence and absence blobs) and consequently an unsupervised approach over sonar imagery in an extensive way can be addressed to count the number of schools in large datasets.
- The school sizing methodology allows to estimate the true dimensions of the school with relatively high accuracy. Still, the proportion of small schools is slightly underestimated and the proportion of medium-large size schools is overestimated.

- Estimated areas are standardized according to the gain model and the scale correction applied based on the sonar range, which are subject to be changed by skippers. These corrections serve to obtain measurable school size estimates in m^2.

- The present methodology classifies the images in an automatic way using the MCM model and focuses on the areas where the probability to find measurable tuna schools is higher.
- The tuna detection, counting and sizing methodology developed in this PhD thesis allows to monitor inter-annual changes of bluefin tuna abundance in at least two different ways: The first one relies on commercial fishing campaigns, from where an index of acoustic detections per unit effort (DPUE) can be elaborated. The second way is based on an annual scientific acoustic survey to sample bluefin tuna presence at the BoB.
- Both applications represent an improvement compared to the status quo, where CPUE is used, that is affected by several tuna-feeding and fleet dependent dynamics, specially during the last years when the series have been interrupted due to quota transfers to other fleets.
- Development of fishery independent abundance indices is an important goal for the Standing Committee on Research and Statistics of the International Commission for the Conservation of Atlantic Tunas (ICCAT). Latest CPUE evaluations underlined the difficulties to accurately track biomass changes (ICCAT 2016b). Currently, no abundance indices are available for the juvenile fraction of the stock in the eastern Atlantic Ocean. Our study contributes towards a fisheries independent index of abundance of the bluefin tuna in the main juvenile feeding area in the Atlantic. As such, it represents an important milestone towards better monitoring of this fraction of the population, and towards a better stock assessment and management of the east Atlantic Ocean and Mediterranean stock.

Ondorioak

Deskribatutako metodologiaren eta aplikazioaren bitartez, beita biziko arrantza ontzietan jasotako sonar irudietan Atlantikoko hegalaburra (AHL) detektatu, zenbatu eta neurtu da. Tesi honen garapenean zehar lortu diren emaitzek ondorengo hipotesiaren balioztatzea ahalbidetu dute:

"Atlantikoko hegalabur taldeak, luzera ahalmen ertaineko sonar irudien analisi automatikoaren bitartez detektatu, zenbatu eta neurtu daitezke, horiek arrantzatzeko kanpaina komertzialetan zein neurtzeko kanpaina akustiko zientifikoetan grabaturiko irudiak erabilita. Horrela, aholkularitza zientifikoaren eta arrantza baliabide honen ikuskapena eta kudeaketa hobetu daitezke"

Jarraian, dokumentu honetan azaltzen diren metodologiaren eta aplikazioaren garapenean zehar ateratako ondorioak erakusten dira. Batzuk, luzera ahalmen ertaineko sonar irudietan AHLaren presentzia/ausentzia detektatzeari dagozkio; besteak, AHL taldeen kontaketa eta neurketari.

Luzera ahalmen ertaineko sonar irudietan AHLaren presentzia/ausentzia detektatzeari dagozkion ondorioak:

- Euskal arrantza flotaren datuak zientzia eta arrantza komunitateen lankidetzari esker jaso dira. Arrantzaleen ohiko jarduna ez oztopatzeko helburuarekin, datuak jasotzeko erabilitako tresneria "kaxa beltz" modura funtzionatzeko diseinatu da. Datuak jasotzeko modu honek arrantzaleen laguntza erraztu eta tesi honetarako zein etorkizuneko proiektu berrietarako datu bilketa ahalbidetu du.
- Sonar irudi prozesaketaren bitartez lortutako *blob*-ei esleituriko hogei ezaugarri morfologikoekin osaturiko datu-baseak hurrengo pausuan aztertutako sailkapen gainbegiraturako egokiak direla baieztatu da.
- Goi eta behe laginketa iragazki bitartez orekatutako datu-baseen eta datu base originalaren artean egindako azterketek erakutsi dute zehaztasun handiagoa lortzen dela goitiko laginketa (SMOTE) aplikatzen duen iragazkiaren bitartez. Ondorioz, AHLaren sonar irudien irudi analisitik eratorritako datu-baseetan iragazki honen erabilera bidezkotzen da.

- Datu-base originala eta ezaugarrien aukeraketa algoritmoek sortutako datu-base murriztuak alderatzeko, sailkapen gainbegiratuak lortutako emaitzak aztertu dira. Emaitza horien arabera, datu base egokiena 20 ezaugarri morfologikoz osaturiko datu base originala da.
- "Atun" eta "Ez-Atun" bezala sailkatutako *blob*-en ezaugarri morfologikoek desberdintasunak erakutsi dituzte. AHL *blob*-ak handiagoak eta zapalagoak dira, eta ardatz horizontalarekiko lerrokatzeko joera erakutsi dute.
- Bost sailkapen algoritmoen eta hiru datu-base desberdinen artean burututako azterketak erakutsi du emaitza onenak Random Forest sailkapen algoritmoaren bitartez eta goitiko laginketa (SMOTE) iragazkia erabiliz lortzen direla.
- Aurkeztutako metodologiak sonar irudietan zehar "Atun" eta "Ez-Atun" kasuak bereizteko gaitasuna erakutsi du, bai eta arrantza kanpaina komertzialetan eta akustikoetan jasotako irudiak lantzekoa ere.

AHL taldeen kontaketa eta neurketari dagozkion ondorioak:

- KAO aplikazioaren bitartez geo-lokalizazioa, abiadura, sonarraren konfigurazioari buruzko balioak, luzera ahalmena eta denbora atera daitezke. Beroriek dira kontaketa eta neurketa metodologia garatzeko oinarrizko informazioa. KAO aplikazioa erabiliz aparteko ekipamendu gehigarrien (GPSa, adibidez) erabilera ekidin egiten da, eta horrek arrantzaleen eta zientzialarien arteko datu trukea bermatzeko helburuarekin bat egiten du.
- Behatzaile zientifikoen bitartez burututako arrantza operazioen ezaugarritzea garrantzitsua izan da metodologia garatzeko eta emaitzak balioztatzeko garaian. AHLaren detekzioak taldekatzeko erabilitako balioak eta behatzaile zientifikoek arrantza ontzietan jaso zituztenak antzekoak direla ikusi da. Ondorioz, metodologiak zuzen ezaugarritzen ditu arrantza operazioak eta egokia da AHLaren zenbaketa gauzatzeko.
- Gure metodologiaren bitartez AHL talde kopuru zehatza estimatu da (34) eta horietako 23 egiazko kasu positiboak (EP) izan dira. Aurrerantzean landu beharreko gaia da hau, eta gezurrezko kasu positiboak (GP) gutxitu behar lirateke.
- Ikerketa honetako datu-base desorekatuan (1/43 presentzia/ausentzia ratioa) lortutako kontaketa emaitzek, metodologia hau jarraituz, AHL taldeen kontaketa modu zabalean aztertzeko eta atun taldeak kontatzeko gaitasuna erakutsi dute.

- Atun taldeen neurketa erlatiboki modu zehatzean burutu daiteke. Dena den, orain arteko emaitzek behe-estimazio arina erakutsi dute AHL talde txikietan eta talde ertain-handiei dagozkien neurriek goitiko estimazioa erakutsi dute.
- Sonar konfigurazio-irabazi desberdinek AHL taldeen neurrietan duten eragina MGO modeloen bitartez estandarizatua izan da. Sonarraren luzera ahalmen aldaketak kontrolatzeko, berriz, eskala faktoreak kalkulatu dira. Neurri horien aplikazioak AHL taldeen neurriak m^2-tan kalkulatzea ahalbidetzen du.
- Metodologia honen bitartez, SMMa erabili daiteke luzera ahalmen ertaineko sonar irudiak modu automatikoan analizatzeko eta, horrela, ikerketaren fokua AHL taldeak egoteko probabilitate handiagoa dagoen eremuetan ezartzen da.
- Tesi honetan garatutako metodologiaren bitartez, AHLaren detekzio, zenbaketa eta neurketak bi modutan sar daitezke espezie honen urteroko monitorizazio prozesuan. Batean, arrantza kanpainetako datuak erabiliz esfortzu unitateko detekzio kopuruan (EUDK) oinarrituriko indizea garatzen da, detekzioak metodo akustikoen bitartez lortuta. Bigarren modua urtero Bizkaiko Golkoan AHLaren presentzia lagintzeko gauzaturiko kanpaina akustikoetan jasotako datuetan oinarritzen da.
- Bi aukera berri hauek aurrerapausoa dira gaur egungo egoerarekin alderatuta; izan ere, gaur egun AHLaren ugaritasuna neurtzeko EUHK indizea erabiltzen da. Indize hori AHLaren gosearen eta arrantza flotarekiko menpekoa denez, ezin izan dira jaso azken urteetako harrapaketa datu serieak, arrantza flotak bere kuota saldu egin duelako.
- ICCATen arabera, arrantza datuekiko independentea den AHLarentzako indizearen lorpena helburu garrantzitsua da. Azkenengo EUHK ebaluaketek biomasa aldaketak jarraitzeko zailtasunak azalarazi dituzte (ICCAT 2016b). Gaur egun ez dago ugaritasun indizerik eskuragarri Ekialdeko Ozeano Atlantikoko AHL jubenilaren populazioarentzako. Gure ikerketak arrantza datuekiko independentea den ugaritasun indize bat eskuratzean du funtsa, eta indize hori Atlantiko osoko AHLarentzako elikatze eremu garrantzitsuenean estimatutako detekzioekin eraikitzen da. Ondorioz, gure ikerketa garrantzizko lehen mugarria da ikerketa eremu honetako AHLaren populazioa monitorizatzeko. Ekarpen garrantzitsua da Ozeano Atlantikoko zein Mediterranioko populazioaren ebaluazio eta kudeaketa egokiagoa lortzeko bidean ere.

Argazkia: Zimarroia gerturatzen. Barranko.2016.

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